Modelling takeover likelihood with statistical matching

Target profile and predictive capability

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Abstract

This thesis introduces statistical matching properly to the research domain of takeover likelihood modelling. Matching is a data pre-processing method aimed at improving causal inferences. Matching was employed to investigate two interrelated areas within the domain, where prior literature has reported varying and inconsistent findings: (1) the determinants of the target firm's takeover likelihood and (2) predictive capability of the takeover models. To investigate the determinants of takeover likelihood, several logit regression models were developed using a training sample of 23 096 firm-year observations on publicly listed US firms between 1999-2013. Predictive capability for the models was measured in an out-of-sample test covering the period between 2014-2018. The findings from the explanatory analysis showed that inefficient management, firm undervaluation, smaller firm size, available free cash flow, lower sales growth and higher leverage increase takeover likelihood, while share purchase activity decreases it. The predictive power was considered low with the most accurate model reporting precision of 1,73% and accuracy of 66,81%. Models using matching consistently reported superior explanatory power compared to the benchmark of no matching. On the contrary, matching had a neutral impact on predictive power. Inconsistency in the explanatory and predictive results of matching suggests a separation between explanatory and predictive analysis of takeover likelihood in terms of methodology. Matching is recommended for understanding the constituents of the target firm's takeover likelihood, but alternative methodology might be superior for predicting future targets.

Keywords: *takeover likelihood, matching, target prediction, M&A modelling*

JEL classification: *G34*

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Contents

1. Introduction

“Mergers and acquisitions, we are always looking for that.”

- *John L. Flannery (American business executive)*

Corporations generally experience several key events throughout their lifecycle, including merger and acquisition (M&A) activity. M&As have the potential to revolutionize the participating firms’ operations, hence substantially impacting their stakeholders. Considering the potential influence of M&A events, it is only logical that the topic has generated broad interest among academia and practitioners. Understanding the tangible profile of acquisition targets would enable more accurate predictions on the future M&A activity, and consequently, improved decision-making for various stakeholder groups. Many acquisitions are explained with speculative concepts of synergies, diversification benefits and empire-building, which neither provide insights on the acquisition participants’ profiles nor can always be quantified. This thesis focuses on (1) explaining the determinants of the target firm's takeover likelihood and (2) predicting future targets.

As M&As impact a wide group of stakeholders with diverse objectives, the distinction between the underlying determinants behind takeover targets and the ability to make accurate predictions is essential. By understanding the characteristics of takeover targets, managers would have the means to measure their firm’s takeover likelihood and take appropriate measures. The improved understanding would also benefit policy makers and regulators in defining M&A regulations or in assessing potential M&A propositions. On the other hand, the predictive capability of future targets would enable investors potentially to earn abnormal returns.

These motives have inspired researchers to attempt deciphering the underlying factors behind takeover targets, and consequently, using the factors to predict future targets. The earliest studies in the field emerged in the late 1960’s, and since then, the subsequent studies have either strived to improve methodological framework or the hypothesized variables behind takeover likelihood. Palepu’s (1986) seminal paper provided a benchmark for future research in the field by standardizing the takeover likelihood hypotheses to cover management inefficiency, firm undervaluation, firm size and growth-resource mismatch. Nevertheless, the results in previous literature have generally produced inconsistent results on the same hypotheses and found low explanatory power for the takeover models. It has been noted that the impactful variables behind takeover likelihood vary over time (Powell, 1997) confirming the need for further research. The inconsistencies and low explanatory power also indicate that all correct determinants of takeover likelihood are likely not found. By improving the methodological framework and exploring new hypotheses, this thesis contributes to the inconsistent findings of target firm determinants.

In order to improve the methodological framework, statistical matching is properly introduced to the field of takeover likelihood modelling. Matching is a method for pre-processing the data (King & Nielsen, 2019) aimed at making two groups as comparable as possible within the applied parameters (Ho et al., 2007). Simply, it allows comparing apples to apples. Matching enables measuring the purer impact of the variables in the regression model by minimizing the confounding effects of other variables. Thus, the causal inferences from the data are enhanced (King & Nielsen, 2019). By improving the balance between targets and non-targets, matching reduces dependence on a specific statistical model, hence reducing researcher discretion and bias (King & Nielsen, 2019). Additionally, multiple matching types are implemented in this thesis adding robustness to the concluded outcomes. While some previous takeover likelihood studies have implemented matching, they have lacked transparency in disclosing the matching methodology and none have measured the impact or compared different matching types. Aligned with the arguments above, there is a strong potential that statistical matching can reduce inconsistencies regarding the determinants of takeover likelihood, and improve the hypothesis validation. This would, consequently, enhance the predictive capability of future targets.

Based on the discussion above, this thesis implements statistical matching to research two interrelated research issues within the domain of takeover likelihood modelling. First, the aim is to improve understanding of the characteristics of takeover targets and evaluate the explanatory power of matching. To improve understanding of targets' characteristics, the existing and widely-used takeover hypotheses are re-examined, and new takeover hypotheses are developed. Second, the predictability of future targets is assessed using publicly available information. Also, the impact of matching to predictive power is evaluated. To reach these objectives, the following research questions are formulated:

> *Q 1A: Do the widely adopted takeover likelihood hypotheses hold at present? And do other additional variables exist which impact takeover likelihood?*
>
> *Q 1B: Does statistical matching improve the explanatory power of takeover likelihood model?*
>
> *Q 2: Does statistical matching improve the predictive performance of takeover likelihood model?*

To answer these research questions, financial data of US firms were used. The motive for relying on the US context is two-folded: first, the majority of previous studies have focused on the US market (e.g. Palepu, 1986; Ambrose & Megginson, 1992; Espahbodi & Espahbodi, 2003; Cremers et al., 2009; De & Jindra, 2012) meaning that the large majority of the included widely-adopted hypotheses are initially developed with the US data. Second, the US context is characterized with well-developed capital markets, substantial data availability and it has historically been the most active takeover market in the world (Sudasanam, 2003; Yılmaz & Tanyeri, 2016). Combined, these reasons make the US setting the optimal choice for this study.

1.1 Contribution/Results of the thesis

As the research questions denote, the focus of this thesis is on two interrelated areas within takeover likelihood modelling. The first part is explanatory aimed at validating the determinants of takeover likelihood and assessing the explanatory power of the models. The covered determinants include six widely-used takeover hypotheses and three supplementary ones. The second part is purely predictive with the main focus on investigating the impact of matching to the model's predictive power.

The determinants of the takeover likelihood were researched as the prior studies have shown inconsistent results using methodologies with potential for improvement. By properly introducing statistical matching to the literature domain, causal inferences are improved, thus providing more robustness to validating the impactful determinants for takeover likelihood. The results found that the takeover likelihood increases with inefficient management, smaller firm size, undervaluation, higher free cash flow, smaller share repurchase activity, smaller sales growth and higher leverage. On the contrary, growth-resource mismatch, tangible assets ratio, revised firm size hypothesis and industry concentration were found insignificant. It was also shown that the explanatory power improved by pre-processing the data with statistical matching.

Predictive power of the takeover likelihood models was tested with an out-of-sample test. The tests were conducted on the various models developed in the explanatory analysis with the aim of estimating how matching impacts the predictive power. The results indicated relatively modest predictive performance with the highest model achieving a precision of 1,73% and an accuracy of 66,81%. Matching did not improve predictive power.

1.2 Structure of the thesis

The rest of this thesis is structured as follows. Chapter two covers the literature domain of takeover likelihood modelling in detail. The relevance of the topic is discussed to various stakeholders and previous studies are covered including the employed hypotheses, results and methodological choices. Chapter three develops the hypotheses for takeover likelihood models. These are grounded in prominent financial literature including prior studies in takeover likelihood modelling. Chapter four introduces the sample and methodological choices employed in this thesis. In chapter five the results are presented from the explanatory analysis. That chapter aims to answer the research question 1A and 1B. Chapter six presents the results from predictive tests and strives answering the research question 2. The results and implications of the results are discussed in chapter seven while chapter eight concludes.

2. Literature review

The literature review chapter focuses mainly on the earlier research on takeover likelihood. First, a wider perspective is taken by providing a brief history of firm event predictions generally (2.1) followed by a discussion on the relevance of takeover likelihood modelling to various stakeholder groups (2.2). Section 2.3 introduces the landscape in detail with a special focus on the hypotheses behind the takeover likelihood models and the achieved results. On the other hand, section 2.4 is dedicated to the methodological choices of prior studies. Section 2.5 introduces statistical matching, which is a key contribution of this thesis.

2.1 The history of firm event prediction

Many researchers have emphasized that a firm experiences a life cycle consisting of several stages which are defined by certain corporate characteristics and events (Mueller, 1972; DeAngelo et al., 2006). These key events, including initial public offerings, mergers and acquisitions, default on obligations and financial distress, are of interest to a firm's stakeholders. The importance of understanding the underlying factors that drive these events and being able to predict whether or not they will occur has therefore not escaped the attention of researchers and practitioners. The inherent assumption in prediction literature is that these events do not occur at random wherefore much attention is given to identifying the underlying factors and their dynamics, and testing whether they can be used for accurate predictions.

From an academic point of view, the study which paved the way for the field of corporate events prediction was conducted by Altman (1968) who attempted to predict corporate default. He developed a model consisting of five accounting ratios constructed of publicly available information and was able to correctly classify 95% of the financially distressed firms in his sample. This sparked the interest of several other papers who continued this research and refined the methodology including Ohlson (1980), Taffler (1984) and Agarwal and Taffler (2008). The research contributed to a greater understanding as to which factors drive firms to become insolvent and subsequently go bankrupt, enabling policy makers to revise regulations and firms to take measures to mitigate risk. The practitioners have, perhaps, had an even greater impact on policy makers and firms as the credit rating agencies Moody's, Standard and Poor's as well as Fitch have long attempted to predict default by firms and countries on their obligations. The prediction of corporate events has since been applied to fields such as credit ratings (e.g. Pinches & Mingo, 1973), returns (e.g. Lewellen, 2004; Campbell & Yogo, 2006), share repurchase (e.g. Dittmar, 2000), loan decisions (e.g. Dietrich & Kaplan, 1982) and takeover likelihood (e.g. Palepu, 1986).

The takeover likelihood literature similarly relies on publicly available financial information in the form of ratios to measure firms' takeover exposure. The interest in identifying takeover targets is substantial for many stakeholders including investors, managers and policy makers. As will be elaborated in section 2.2 much of the interest is directed towards understanding which firms are likely to become acquired wherefore the literature has predominantly focused on understanding the characteristics of, and predicting, target firms (e.g. Simkowitz & Monroe, 1971; Palepu, 1986; Ambrose & Megginson, 1992; Powell & Yawson, 2007; Danbolt et al., 2016). However, there are exceptions where studies have taken an alternative approach and attempted to predict acquiring firms (Cornett et al., 2011) and/or used firms' takeover likelihood as an independent variable while investigating completely other topics including its impact on firm valuation (Cremers et al., 2009). This study focuses on the event of corporate acquisitions by investigating whether employing various matching methodologies can improve prediction accuracy.

2.2 Relevance of takeover likelihood

Understanding the variables behind takeover likelihood and predicting takeovers accurately is of interest to various stakeholders. Key identified stakeholder groups include management, investors and researchers using takeover likelihood as an independent variable. The relevance of takeover predictions for them are discussed below. Other stakeholder groups include for instance policy makers and regulators who could utilize the insights in decision-making.

2.2.1 Management

For management, the prediction of takeover targets is of relevance at least due to two reasons: (1) acquisitions often involve replacements in the management team and (2) M&A activity has the potential of altering the industry structure. Thus, the ability to predict acquisitions increases understanding of the future industry structure, possibly improving the decision-making.

Firstly, according to previous financial research, acquisitions can enhance value when ineffective managers are disciplined (Haleblian et al., 2009). It is one of the key motivations behind value creation from acquisitions, and consequently, value creation is a key motivation for acquisitions (Haleblian et al., 2009). Also, much of the previous research on takeover prediction has hypothesized ineffective management to increase the likelihood of becoming an acquisition target (Palepu, 1986; Brar et al., 2009; Cremers et al., 2009). On the same lines, advocates of the agency theory take the perspective of shareholders and reason that acquisitions might protect shareholders from inadequate management (Jensen, 1986; Jensen & Ruback, 1983). Consistent with these, previous studies have indeed found that target firm CEOs are often dismissed after completion of an acquisition (Agrawal & Walkling, 1994; Martin & McConnell, 1991) and that top management turnover are much higher than in their benchmark companies - on average 59% of the top management is replaced (Walsh, 1989). Generally, managers resist takeovers; this is partially due to their willingness to keep their positions but also due to their belief the firm has hidden values and that the resistance would increase the offer price (Ruback, 1987). Therefore, predicting the acquisition likelihood of the management team's own company would allow them to take appropriate measures to either prevent the takeover or to increase the acquisition price.

Secondly, M&A activity might affect industry dynamics in various ways. For instance, a merger within the same industry reduces the number of operating companies and consolidates the industry; an acquisition might increase the resources of a key player in improving their ability to capture market share; or a new player with vast technological capability might enter the industry via an acquisition. Decreased competition as a result of a takeover increases acquiring company's market power, which previous finance literature has linked to increased equity value (Devos et al., 2009). Increased market power allows companies to charge customers higher prices (Devos et al., 2009). Further, firm performance is affected by both company-specific factors (referred to as the resource-based view) and industry factors (eg. Galbreath & Galvin, 2008). Understanding the dynamics of the industry including the forces that impact competition are at the core of developing a strategy for a company as the industry shocks pose some of the most significant opportunities and threats for the company (Porter, 2007). Thus, the ability to predict M&A activity in an industry would allow managers to better understand the future industry structure, and hence, improve strategic decision-making.

2.2.2 Investors

Takeover likelihood modelling is a relevant topic of research for investors in their pursuit to generate abnormal returns. As M&A activity often leads to a substantial change in the involved companies, both the acquirer and target, it has the potential to significantly impact the stock price. Consequently, excess returns associated with acquisitions have cultivated wide popularity in both academia and practice. The previous research has consistently shown significant positive abnormal returns for acquired companies (Jensen & Ruback, 1983; Jarrell et al., 1988; Schwert, 1996; Andradeet al., 2001; Yilmaz & Tanyer, 2016) while the findings have varied for acquiring companies from significant abnormal returns (Yilmaz & Tanyer, 2016) to non-significant negative returns (Andrade et al., 2001).

Furthermore, a common trend in the previous literature has been the magnitude of the returns for targets - many studies have concluded significant double-digit abnormal returns. In their widely cited research paper, Andrade et al. (2001) studied acquisitions in the US between 1973-1998 and found that targets generated on average 16% abnormal returns in a short window (from one day before to one day after the acquisition announcement) and 23,8% on a longer window (from 20 days prior to the close of the merger). These results were stable across the studied decades. In a more recent study, Yilmaz and Tanyer (2016) found an average excess return of 11,37% for American targets during 1992-2011, which was in line with the returns of their global sample. On the contrary, the findings of these two studies regarding the abnormal returns of the buyer reflect the less coherent view in the literature. While Andrade et al. (2001) didn't find significance for acquiring companies' negative returns, Yilmaz and Tanyer (2016) showed modest 1,38% excess returns (significant). Additionally, Malmendier et al. (2018) compared buyers to the losing bidders in the same acquisitions process and found that the losers outperformed the successful buyers post-merger.

The discussion above indicates that investors might be able to generate abnormal returns by identifying and investing in takeover targets before the acquisition announcement. High returns for acquisition targets and consistency in the findings might explain why the topic of predicting takeover targets for an investment strategy has received attention in the previous research. Although, the results from these studies have varied: insignificant negative returns (Palepu, 1986), insignificant positive returns (Powell, 2004), significant negative returns (Powell, 2001) and significant positive returns (Brar et al., 2009; Cremers et al., 2009). By improving the accuracy of the acquisition target predictions, would allow a higher ratio of the investments to be assigned to de facto the acquired companies instead of the falsely predicted targets (i.e. type 2 errors). This should shift the investment returns towards the average returns of the acquired companies.

2.2.3 Research: takeover likelihood as an independent variable

During the past decade, researchers have started to utilize takeover likelihood as an independent variable in their models. The main objective of these studies is not to predict the likelihood of acquisition itself but to utilize the likelihood to investigate other research questions. Studies include, for example, Cornett et al. (2011), Bhanot et al. (2010) and Cremers et al. (2009). As these studies employ takeover likelihood as an independent variable, they implicitly assume that the takeover likelihood prediction model is sufficient and can accurately predict the acquisitions. Especially considering the inconsistencies in the previous research of acquisition likelihood (discussed more in section 2.3), the studies utilizing the likelihood as an independent variable might be concluding false findings. Thus, considering the trend with acquisition likelihood as an independent variable, it is important to continue research on plain acquisition likelihood in order to improve the understanding of its constituents and make a sound ground for the future research in other areas utilizing the takeover likelihood.

2.3 Previous studies modelling takeover likelihood

The importance of takeover prediction and its relevance to various stakeholders was discussed in the previous section. The objective of the current section is to provide an overview of the key papers within the takeover likelihood literature. Given the long history and broad nature of the field, the studies were divided into three separate eras. These are not clearly distinct from one another but the studies produced within each era share significant similarities in terms of methodology and general approach. The eras include the

Pre-Palepu era, which consists of studies published prior to 1986, the Palepu era covering the period between 1986 and 2006, and the Modern era stretching from 2007 until the present. These eras are presented in chronological order: the Pre-Palepu era is covered first in section 2.3.1, followed by the Palepu era in section 2.3.2, and ultimately the Modern era in section 2.3.3. The sections are subsequently divided into overview and studies. The overview section provides a big picture of the development within the field during the era. The studies section provides a more detailed description of the most important studies during the era.

2.3.1 Pre-Palepu era

Overview

The first studies in takeover likelihood literature were motivated by the interest from stakeholders including legislators, investors, managers and researchers. The initial papers of this era predominantly focused on identifying and understanding the characteristics of takeover targets. As the literature gradually evolved, the researchers continued to investigate the underlying factors driving takeovers, but they started also applying this knowledge in predicting future targets. Many of the hypotheses behind the included factors were, however, arbitrarily selected based on the individual researchers' preferences, and thereby, varied substantially between studies. However, with the growth of the field, increasingly more attention was also directed towards improving methodological choices as researchers started addressing some of the weaknesses present in previous studies. That led to some early success, where researchers such as Stevens (1973) succeeded in achieving an accuracy score of 67,5% and 70%. Although the results indicated that substantial progress had been made, Palepu (1986), among others, argued that this was only the case due to several methodological flaws incorporated in the studies. He further criticized the studies for lacking theoretical support in the hypotheses/variable selection process, something he later introduced.

Studies

The earliest study focusing on the area of takeover likelihood was conducted by Hayes and Taussig (1968). They set out to find an explanation of the motives behind cash takeovers, as they had increased over five hundred percent during the last decades. This phenomenon had left investors, legislators, financiers and academics puzzled. Their central hypothesis assumed that target firms' assets were undervalued due to inefficient management or because of overly conservative accounting policies. With a sample size of 50 randomly selected US target firms, and equally many non-targets, the authors conducted a univariate analysis on accounting ratios such as book value of equity to the market value of equity, inventory to total assets, and net fixed assets to total assets. The results showed that accounting policies and overly conservative policies do not affect a firm’s likelihood of being acquired. Instead, firms with an excess of liquid assets, low return on net worth, and unstable or declining dividend ratio tended to be associated with a higher takeover likelihood.

Vance (1969) followed the research proposed by Hayes and Taussig (1967) and set out to create a self-use formula for managers of industrial companies to use in order to predict their own firm’s takeover vulnerability. Vance was convinced that predicting a firm’s takeover likelihood with publicly available information was possible by stating that “*Managers should realize: many if not most of the take-overs or tenders could have been foreseen by looking at the victim’s published financial data*.” (Vance, 1969, p.93). To conduct the study, he relied primarily on four aspects of a firm’s financial position, its liquidity, debt position, P/E-ratio and stability of earnings. Although Vance admitted that non-financial variables affect a firm’s likelihood of being acquired, no such variables were included. The results were positive as Vance succeeded in predicting 17 firms correctly out of a sample consisting of 21 target firms.

Monroe and Simkowitz (1971) criticized the methodology employed in earlier studies by presenting new financial ratios and introducing a stepwise discriminant analysis. The authors started with 24 firm-specific financial and non-financial characteristics in order to distinguish future targets from non-targets. The results suggested that takeover firms were characterized by paying lower dividends, tended to be smaller in size, experienced lower growth in equity and had a lower P/E ratio. Furthermore, the authors were one of the first to observe and mention that non-financial ratios were important in takeover prediction.

Stevens (1973), in turn, sought to improve the methodology by Monroe and Simkowitz (1971) as he argued that the high levels of multicollinearity invalidated the results of their variable selection process. To conduct the study, Stevens adopted a Multiple Discriminant Analysis (MDA) model due to its success in related fields (e.g. bankruptcy prediction) and its ability to rank variables based on their capacity to distinguish takeover firms from non-takeover firms. The financial ratios employed were ultimately selected based on a principal component analysis. That was done to mitigate the issue of multicollinearity by reducing the model's dimensions to a lower number of explanatory variables. These variables differed from the ones used by Monroe and Simkowitz (1971) and proxied for leverage, profitability, liquidity and activity. The results were overwhelmingly positive as the author achieved an accuracy ranging between 67,5% and 70%, although no real holdout sample was used. Monroe (1973) soon replied with a comment regarding potential improvements for Steven’s paper. He suggested that Stevens should have also assessed the financial significance of his model as opposed to solely focusing on its statistical significance.

Wansley et al. (1983) addressed this criticism launched by Monroe (1973), namely, to study the financial impact of investing in firms with the characteristics of target firms. The authors initially started with 20 financial variables from 10 different categories but narrowed them down to P/E-ratio, leverage, natural logarithm of net sales, sales growth and market value of equity to total assets due to the theoretical arguments and findings of Banz (1981), Simkowitz and Monroe (1971) and Stevens (1973). Together with linear discriminant analysis, the authors managed to achieve an accuracy score of 69,2% on a holdout sample.

2.3.2 Palepu era

Overview

The second era started with Palepu's seminal study from 1986, where he presented a detailed critique regarding the methodological approach and hypotheses development process of previous studies. Palepu (1986) contributed to the field in two ways: (1) he addressed multiple methodological shortcomings in prior studies related to e.g. statistical model, selection of cut-off point in target prediction, sample construction, and (2) he introduced a more robust and theoretically dependent hypothesis development process. His results showed that the findings of the previous era, where the studies achieved high accuracy scores in target prediction, could be attributed to these methodological weaknesses.

The impact of his study is hard to ignore as it became the benchmark to extend or improve for future studies. Accordingly, the following studies tended to be directed towards adding new independent variables (e.g. Ambrose & Megginson, 1992; Walter, 1994; Powell, 1997) or suggesting improvements of the methodology (e.g. Walter, 1994; Barnes, 2000; Powell, 2001). Two of the most successful studies in extending the number of widely adopted hypotheses were Ambrose and Megginson (1992) and Powell (1997), who introduced two hypotheses, which became widely adopted. One striking observation is, however, the inconsistency in hypothesis validation as most studies tended to include many of the same independent variables but yielded different results in terms of significance. This discrepancy can perhaps be attributed to the differences, or weaknesses, in methodologies across the studies.

Many of the studies also tested the predictive power of their models and attempted to create investment strategies based on their predictions. This strategy predominantly yielded a negative abnormal return, a swift change from some of the more positive results produced in the Pre-Palepu era. That should perhaps not come as a surprise as the methodologies of the older studies included questionable choices. Barnes (2000) and Powell (2001), to name a few, thus agreed with Palepu (1986) in his conclusion that it is unlikely that an investment strategy based on investing in targets can yield a positive abnormal return.

Espahbodi and Espahbodi (2003) ended the era by starting a new strand of research focused on investigating the impact of various statistical models on takeover likelihood modelling by assessing their ability to correctly predict takeover targets.

Studies

One of the most cited articles within all studies in the field was created by Palepu (1986). His paper contributed to the field in two ways: first, by challenging some of the methodological choices made by researchers in takeover likelihood and bankruptcy prediction literature, and second, by proposing theoretically-driven variable selection for modeling takeover likelihood. The first contribution highlights methodological flaws in prior research, namely (1) the use of non-random equal share samples in model estimation, (2) reliance on arbitrarily selected cut-off points in target prediction and (3) reliance on equal-share samples in prediction tests. These, and other methodological choices of previous studies, are elaborated further in section 2.4. Second, Palepu (1986) proposed that the variable selection process should be theoretically dependent on pre-specified hypotheses. This was in contrast to some of the prior research, where the variable selection was often arbitrary based on e.g. a stepwise procedure by Simkowitz and Monroe (1979). Palepu argued that, by employing a hypothesis-driven variable selection process, a potential overfitting problem could be mitigated. That is because variables would no longer be dependent on the sample but on prominent financial literature. Palepu (1986) included six hypotheses based on widely adopted theories in financial literature. The hypotheses were (1) inefficient management, (2) firm size, (3) market-to-book (MTB), (4) growth-resource mismatch, (5) industry disturbance, and (6) price-earnings (P/E) ratio. These hypotheses argued that takeover firms tend to be inefficiently managed, smaller in size, undervalued, experience a mismatch between their future growth opportunities and the resources needed to finance them, operate in an industry with an active takeover market, and have a low price-earnings ratio. The results of the study suggested that all hypotheses were significant except for MTB and P/E-ratio.

Ambrose and Megginson (1992) were among the studies to extend the hypotheses developed by Palepu by adding variables associated with asset structure, takeover defenses, insider and institutional shareholdings. Their results showed that targets were significantly smaller compared to non-targets in terms of size, had a higher ratio of fixed assets to total assets and had a smaller net increase in institutional ownership in the quarter prior to a takeover-bid. However, most of the hypotheses proposed by Palepu were proven insignificant and the model had low explanatory power. No predictions were made in this study.

Walter (1994) employed the same methodology as Palepu (1986) and incorporated most of the same hypotheses. He introduced new variables of asset-turnover, dividend payout, inflationary tax loss, and tax savings. Walter (1994) found that Market-to-book was the most important variable in distinguishing target from non-target firms while size, asset turnover and industry closely followed. These results were inconsistent with Palepu's (1986) findings as the market-to-book ratio was one of the few variables he failed to validate. All other variables were found insignificant and were filtered out from the final model, which achieved an accuracy score of 72,53%, although only 22,22% of predicted targets were actual targets.

Powell (1997) likewise adopted the hypotheses developed by Palepu (1986) and complemented them with Ambrose and Megginson's (1992) tangible assets ratio, and his own free cash flow hypothesis. When testing the discriminatory capabilities of the models, he found that the significant variables varied over time. The best performing variables from a statistical perspective were firm size closely followed by market-to-book, sales growth and liquidity. However, in accordance with the results of previous studies, Powell (1997) found that all of his models had low explanatory power. He attributed the poor results to one of two things; either the theories used by Palepu in his hypothesis development lack theoretical validity or the proxies used to measure the theoretical constructs failed to do so.

Barnes (2000) extended the work of Palepu (1986) by adjusting the cut-off point to yield better financial returns. His theory was that the number of falsely classified non-targets as targets was the fundamental reason why Palepu (1986) failed to generate an abnormal return. To empirically test the proposed improvement, he relied on industry adjusted versions of the hypotheses developed by Palepu (1986), with the exception for the industry disturbance hypothesis. He found that ratios concerning profitability in Palepu's inefficient management hypothesis and sales growth in the growth-resource mismatch hypothesis, were considered statistically important in the prediction of targets. None of his models, both the general model using non-industry adjusted financial variables and the model with industry adjusted financial variables, successfully classified a single target.

Also, Powell (2001) tested whether adjustments to the cut-off methodology model proposed by Palepu (1986) could generate abnormal returns. To test these improvements, he relied on the hypotheses inefficient management, firm undervaluation, firm size and growth-resource mismatch developed by Palepu (1986), asset structure developed by Ambrose and Megginson (1992) and Free cash flow developed by Powell (1997). No significance testing was conducted. When testing the developed models on an out-of-sample dataset from 1996, his best performing model classified 216 firms as potential targets, whereas only seven received a bid. Despite the suggested methodological improvements, the study yielded a negative return abnormal return.

Espahbodi and Espahbodi (2003) investigated the predictive ability of numerous statistical models. The tested models included both non-parametric (recursive partitioning) and parametric models (logit, probit and discriminant analysis). The employed financial hypotheses were similar to Palepu's (1986) study. They were complemented with new non-financial hypotheses, including defensive strategies, anti-takeover regulation and the directors' ownership. As the authors employed a stepwise variable selection technique, the number of included variables was reduced to four. The chosen variables included free cash flow to total assets, the existence of golden parachutes, a location-specific dummy and market value of equity to total assets. The two first variables achieved the highest significance scores. A non-parametric recursive partitioning model had the highest accuracy score of 66% followed by logit (52%), probit (52%) and DA (51%) models. However, previous research has shown that the recursive partitioning model has been inconsistent in its prediction performance (Espahbodi et al., 1998), which indicates that the results could be sample-specific or arise due to differences in methodology.

2.3.3 Modern era

Overview

The results from the Palepu era could not form profitable investment strategies by investing in predicted targets due to a high number of type 2 errors (non-targets misclassified as targets). An important focus during the modern era was aimed at reducing type 2 errors. That was done by either investigating whether the choice of statistical model could improve predictive capabilities or by introducing new hypotheses.

Regarding the statistical models, the performance differences between parametric and non-parametric models were evaluated. The researchers proposed that the common statistical models employed in previous studies were inferior to the more advanced classification techniques available in the machine learning field. The findings of Ouzounis (2009) proved that certain non-parametric models could provide abnormal returns. However, they failed to demonstrate their superior performance over parametric models.

The studies in the modern era implicitly acknowledged that the hypotheses proposed by Palepu (1986), and extensions by Ambrose and Megginson (1992) and Powell (1997) provided a solid foundation. New variables were included in the models aimed at reducing classification errors. None of the newly developed hypotheses have yet received a broad adoption.

Furthermore, an additional and somewhat separate strand of research emerged during this era, which uses takeover likelihood as a key input variable to explore new research questions. The researchers in this subfield relied on a similar approach as studies in the previous era. They did not seek to further improve the methodology in terms of adding new hypotheses or trying different statistical models. Although Cremer et al. (2009) tested whether an abnormal return can be achieved, these three studies fail to test the predictive performance of the developed models in terms of future targets. However, the emergence of using takeover likelihood as an input variable indicates the importance to improve its methodology and predictive capabilities further.

Studies

The research comparing the performance of parametric and non-parametric models (see Espahbodi and Espahbodi, 2003) was continued by the UK studies Ouzounis et al. (2009), Pasiouras et al. (2007) and Pasiouras et al. (2010). Ouzounis et al. (2009) added a divided policy hypothesis to the standard hypotheses combination initially proposed by Palepu (1986). The findings of Ouzounis (2009) proved that certain non-parametric models could provide abnormal returns across an entire holding period but failed to demonstrate that they have consistently superior performance compared to parametric models. This finding was further strengthened by the results produced by Pasiouras et al. (2007) and Pasiouras et al. (2010).

Powell and Yawson (2007) set out to investigate why takeover prediction literature was plagued by type 2 errors and if various industry-related variables could help explain corporate restructuring events. They combined four new industry-specific variables with Palepu's (1986) hypotheses (except industry disturbance and price-earnings ratio), tangible assets hypothesis by Ambrose and Megginson (1992) and free cash flow hypothesis by Powell (1997). Their results indicated that many misclassification errors could partially be attributed to other restructuring events. Therefore, the historically used hypothesis combinations do not fully capture the target firm's characteristics and additional hypotheses might be required. They further argued that by using a multinomial model, misclassification errors could be reduced but not eliminated.

Brar et al. (2009) primarily investigated the profitability of investing in predicted targets. They extended Palepu’s (1986) hypotheses by incorporating more technical variables in order to better capture the timing of the expected acquisitions. These technical variables included trading volume, momentum and a measure of market sentiment. They found that target firms were characterized with a smaller size, lower revenue growth, undervaluation, stronger price momentum over the short term, being less liquid, and actively traded prior to acquisition. The results proved that the model had an accuracy score of 71,7%, ultimately leading to a profitable investment strategy with an unadjusted return of 17,4%. Noteworthy is that criticism has been directed towards the methodology employed by Brar et al. (2009) as they used an in-sample test for predictive performance creating a considerable look-ahead bias into the findings.

Danbolt et al. (2016) focused on investigating why portfolios of predicted takeover targets tend to underperform. They hypothesized that type 2 errors (misclassified non-targets) underperformed relative to the typical non-target firms, and by avoiding them, positive abnormal returns could be generated. They relied on the widely-used hypotheses of the Palepu era by Palepu (1986), Ambrose and Megginson (1992) and Powell (1997). By screening the predicted targets for size, leverage and liquidity to eliminate likely-to-bankrupt firms, the authors succeeded in generating significant positive abnormal returns.

Using takeover likelihood as an input variable

A new strand of research emerged during this era where studies estimated takeover likelihood and used it as an input variable for a range of other empirical research. Cremer et al. (2009) investigated what impact takeover likelihood had on firm valuation and whether it could be a profitable investment strategy. To estimate the takeover likelihood they developed their own logit model by relying on the hypotheses firm undervaluation, firm performance, size, leverage developed by Palepu (1986), free cash flow by Powell (1997), asset structure ratio developed by Ambrose and Megginson (1992), and proxies for shareholder control suggested by Shleifer and Vishny (1986). Cremer et al.'s (2009) investment strategy of investing in firms with the highest takeover likelihood and shorting the ones with the lowest likelihood achieved an abnormal return of 11,77% relative to the four-factor Fama-French. It is worth noting that Cremer et al. (2009) did not test his model using a hold-out sample.

Bhanot et al. (2010), on the other hand, investigated whether the relationship between stock returns and bond spreads is affected by takeover likelihood. To model takeover likelihood the researchers relied on the hypotheses firm size, firm undervaluation, firm performance, leverage, percentage of institutional ownership, one-year price volatility, R&D and asset structure. No validation tests were conducted to investigate the model's predictive capabilities.

Cornett et al. (2011) investigated whether the takeover likelihood, proxy for investor anticipation of merger, plays a role in the wealth distribution between bidder and target shareholders in the event of a merger. To estimate the likelihood of takeover, the researchers relied on a logit model and the hypotheses of sales shock, firm size, industry concentration, growth-resource mismatch, performance, free cash flow, price run-ups, information asymmetry and previous mergers. No further validation tests were conducted to investigate how accurate the model was at predicting takeover targets.

2.4 Methodological choices in previous studies

The previous section introduced the past studies in terms of prediction hypotheses; that is, the variables expected to impact the takeover likelihood. These variables were sequentially used as input for the quantitative model to produce takeover likelihood estimates. This section focuses on the quantitative models and other important methodological choices applied in the previous literature. These include 2.4.1 the quantitative model, 2.4.2 sampling and matching, and 2.4.3 methods related to predictions. The same time periods are used to categorize the previous studies as in the prior section: pre-Palepu, Palepu and modern era. Palepu (1986) criticized and made significant improvements to the methodologies used in earlier studies setting the baseline for future research, while during the modern era researchers started using panel data as sampling method and utilizing acquisition likelihoods as independent variables to study other research questions. Table 2.4 summarizes the important methodological choices of previous studies.

Table 2.4: Methodological choices of previous studies

Study	Country / region	Type of study	Quantitative Model(s)	Training sample construction	Holdout sample construction
Hayes and Taussig (1967)	USA	Characteristics	Linear Model	Equal	-
Stevens (1973)	USA	Prediction	Linear Model	Equal	Insample
Wansley et al. (1983)	USA	Prediction	Linear Model	Equal	Equal
Dietrich and Sorensen (1984)	USA	Prediction	Logit Model	Ratio (2x)	Ratio (2x)
Palepu (1986)	USA	Prediction	Logit Model	Equal	Natural proportions
Bartley and Boardman (1990)	USA	Prediction	Linear Model	Natural proportions	Insample
Ambrose and Megginson (1992)	USA	Characteristics	Logit Model	Natural proportions	-
Walter (1994)	USA	Prediction	Logit Model	Natural proportions	Natural proportions
Powell (1997)	UK	Characteristics	Logit Model	Equal	-
Espahbodi and Espahbodi (2003)	USA	Prediction	Logit Model, Linear Model, RP, Probit Model, QDA	Ratio (3x)	Ratio
Powell (2004)	UK	Prediction	Logit Model, Multinomial Logit Model	Panel data	Natural proportions
Ouzounis et al. (2009)	UK	Prediction	Linear Model, ANN, UTADIS, SVM	Equal	Natural proportions
Brar et al. (2009)	EU	Prediction	Logit Model	Population	Natural proportions
Cremers et al. (2009)	USA	Prediction	Logit Model	Panel data	-
Cornett et al. (2010)	USA	Prediction	Logit Model	Panel data	-
Bhanot et al. (2010)	USA	Prediction	Probit Model	Panel data	-
De and Jindra (2012)	USA	Characteristics	Multinomial Logit Model	Natural proportions	-
Edmans et al. (2012)	Global	Characteristics	Linear Model	Panel data	-
Danbolt et al. (2016)	UK	Prediction	Logit Model	Panel data	Natural proportions
Anagnostopoulos and Rizeq (2019)	USA	Prediction	Logit Model		Equal
Tunyi et al. (2019)	UK	Characteristics	Logit Model	Panel data	-

Note: The table presents the methodological choices of previous studies in terms of statistical model employed, training sample construction and holdout sample construction. The list includes a majority of the takeover likelihood studies referenced in this thesis but is not exhaustive. The study column is the author(s) and the year of publication. The country / region is the country or region of the data. Type of study is either characteristics (research of only the determinants of takeover likelihood) or prediction (future targets were predicted). Abbreviations within the quantitative models column include Artificial Neural Network (ANN), Probabilistic Neural Network (PNN), Quadratic Discriminant Analysis (QDA), Recursive Partitioning (RP), Support Vector Machines (SVM) and UTilities Additives DIScriminante (UTADIS). For training sample and holdout construction the alternatives include: equal (same number of targets and non-targets in the sample), ratio (number of non-targets is multiplied with certain coefficient defined in the parenthesis), natural proportions (targets to non-targets represent the true ratio), panel data (use of firm years instead of firms - natural proportions) and insample (the predictive performance defined on an insample test).

2.4.1 Quantitative model

The quantitative models used in the takeover prediction literature can briefly be divided into two main categories. Firstly, parametric models include the most widely used statistical models including univariate models, linear discriminant models, logit and probit models. These have gained the most popularity in the takeover prediction research throughout the decades (eg. Stevens, 1973; Palepu, 1986; Powell, 1997; Brar et al, 2009; Danbolt et al., 2016). Parametric models are a broad group of statistical models in which all of the information content is incorporated into the parameters (Zellner et al., 2001). Secondly, non-parametric models have gained increasingly more interest with increased computing power. While parametric models have an ex-ante defined model structure (for example linear), non-parametric models determine that from the data (Zellner et al., 2001).

The (possibly) first research article on the takeover prediction domain utilized a simple univariate model in the analysis (Hayes & Taussig, 1968). Otherwise, the Pre-Palepu era was characterized by linear models in terms of the employed quantitative model (eg. Stevens, 1973; Wansley et al., 1983). Later, linear discriminatory models (LDM) were argued in the literature to be less-suitable for takeover prediction (eg. Palepu, 1986) and they were replaced with theoretically superior models. The critique of linear models was pointed, for example, towards the inherent assumptions underlying the models, which were often violated in previous research (Zavgren, 1983; Barnes, 1999). After Palepu's (1986) influential paper criticized the use of LDM on takeover prediction and suggested using logit models instead, logit models became the new norm in the takeover prediction research. The superiority of logit models compared to LDM has been credited to less restrictive assumptions. The logit model avoids the normality assumption of the LDM model concerning independent variables (Barnes, 1999) - many of the independent variables are financial / accounting ratios, and thus, not normally distributed (Barnes, 1990). The logit model neither requires a linear relationship between the dependent and independent variables but can account for non-linearities, hence likely to specify the model parameters more correctly. Additionally, the logit model's output is directly interpretable as it is scaled between 0 and 1 (Brooks, 2019) unlike LDM's unbounded output. Some studies (e.g. Espahbodi and Espahbodi, 2003; Bhanot et al., 2010) have also utilized probit models in takeover prediction. Based on Brooks (2019), probit and logit models both are preferred to the linear models and the yielded relationships between dependent and independent are very similar between the models.

During the Modern period of takeover prediction literature, the logit models have remained the most widely used quantitative model. Researchers have also experimented with non-parametric models, such as support vector machines (SVM) and artificial neural networks (ANN), and directly compared them to logit and LDM models. The results from the comparisons are varied: Espahbodi and Espahbodi (2003) reported non-parametric models to outperform the logit model in an in-sample classification test but to underperform in an out-of-sample test. On the other hand, Ouzounis et al. (2009) found non-parametric models to perform better compared to LDM. While non-parametric techniques outperformed LDM in Ouzounis et al.'s (2009) study, no conclusions were made for the logit model (which theoretical superiority against LDM was discussed above). The authors further praised the non-parametric techniques’ characteristic of not having to postulate various assumptions as prerequisites as the model determines the structure from the data. On the contrary, Espahbodi and Espahbodi (2003) argued that this flexibility of non-parametric models might also be disadvantageous as they become highly user-specific. That is because they are sensitive for hyperparameter choices such as the number of splits and splitting values. The indication might be that the non-parametric models were too strongly tuned for the training set, and thus, underperformed the logit model in the holdout set.

Anagnostopoulos and Rizeq (2019) studied the takeover prediction of technology companies using the logit model and multilayer perceptron model (MPM). Their findings of MPM having better performance are not, however, valid as the holdout sample used for MPM was 23 companies compared to the test set of 226 companies for the logit model. Generally, for explanatory purposes, non-parametric models are inferior compared to parametric models in the interpretation capabilities. Non-parametric models are solely focused on results but are incapable of providing equally meaningful information on the relationship between independent and dependent variables as parametric models (Espahbodi & Espahbodi, 2003). Since this study strives to interpret and understand the variables behind takeovers, non-parametric models are not suitable, and the most prominently used parametric model, logit regression, is employed in the analysis.

2.4.2 Sampling

In this subsection, the important methodological choices of previous literature regarding sampling are discussed. These include differences in the sample itself (geographical areas, time periods and sample sizes), and construction of the training and holdout samples.

Samples

Most of the previous studies in takeover likelihood have been conducted using data from the US including the most prominent study in the field conducted by Palepu (1986). In the late 1990s and early 2000s, the topic gained increased popularity in the UK especially with studies undertaken by Powell in 1997, 2001 and 2004. In the modern period, studies have been conducted predominantly with data from the US (e.g. Cremers et al. 2009; Bhanot et al., 2009; De & Jindra, 2012), Europe (Brar et al., 2009) and the UK (Danbolt et al., 2016; Tunyi et al., 2019).

The length of time periods included in the study and sizes of the datasets have increased throughout the years. While the studies in the pre-Palepu period consisted of only less than 100 firms and covered a few years, the studies in the modern era have typically had datasets of many thousands of companies covering approximately two decades.

Train-test split

Two main methods for splitting the dataset into training and testing subsets can be identified from the previous literature: non-true out-of-sample and true out-of-sample. Some of the earlier literature during and slightly after the pre-Palepu era did not split the dataset at all into training and holdout sets but simply conducted the prediction tests with the same in-sample data (e.g. Stevens, 1973). A more advanced method without a clear-cut holdout sample was used, for example, by Bartley and Boardman (1990), who employed the Lachenbruch U method. They described the splitting as: "The Lachenbruch U method (a jackknife procedure) classifies each observation using a MDA model estimated from all other observations. This process is repeated sequentially for the entire sample" (Bartley & Boardman, p.63, 1990). Danbolt et al. (2016) adopted a recursive approach also without a true holdout sample. They developed the model using the entire dataset, and then tested the predictive capabilities with a rolling window method using the same data. The rolling window approach entailed training the model, for example, with data from periods 1-5 and testing the model with period 6, then training the model with periods 1-6 and testing with period 7 and continuing the same approach until the last period is tested. The downside with all of these approaches is that the model is never tested with truly unseen data. Despite the rolling window approach and Lachenbruch U method do not train the "test set" (meaning that the observation/period of observations are left untrained for predictions), bias might arise from having used the data earlier in developing the model.

The prevalent method throughout the history of takeover prediction literature has been to split the dataset based on a specific year - generally, the last year of data has been assigned as the holdout sample (e.g. Palepu, 1986; Powell, 2004; Ouzounis et al., 2009). As an example, data from years 1-5 would be used to train the model and year 6 to test the predictive capability in an out-of-sample test. This method is referred to as a "true out-of-sample" split in this paper. Previous studies have used different holdout periods from 1-year (Palepu, 1986) to multiyear (Brar et al., 2009) to having different holdout periods for targets and non-targets (Espahbodi & Espahbodi, 2003). This method simulates the unknown future data by leaving the specific holdout sample completely untouched before the prediction test. After all, classification model's real test is to classify observations correctly in the future (Espahbodi & Espahbodi, 2003), and therefore the true out-of-sample split is used in this thesis.

Training sample

The sample construction in takeover prediction literature revolves heavily around the important question of how to select appropriate distribution of targets and non-targets. The rare occurrence of takeovers poses a challenge in terms of extracting enough information in the training phase and creating realistic circumstances for prediction. The sampling methods of previous studies can be broadly divided into two main categories of matching (observations in firms) and panel data sampling (observations in firms years).

Matched samples were the standard in the literature during the pre- and Palepu eras while some studies have used matching in the modern era as well (e.g. Brar et al., 2009; De & Jindra, 2012). Earlier studies in takeover prediction aimed to alleviate the rare-event problem of takeovers by using equal samples, i.e. having an equal number of targets and non-targets (e.g. Stevens, 1973; Wansley et al., 1983; Powell, 1997). Palepu (1986) argued that this is a valid method as a random sample would have low information content due to the small number of takeover targets at a population level. On the other hand, Bartley and Broadman (1990) criticized the use of equal-sized samples for targets and non-targets arguing that the approach leads to biased estimates. This is due to the distribution of targets and non-targets does not reflect reality, thus biasing the relationship between dependent and independent variables. The equal-sized training samples, and consequential heavy bias in the distribution of targets, might partially explain (together with other factors such as holdout sample construction and cut-off probabilities discussed in later sections) why the majority of Palepu's (1986) out-of-sample predictions were misclassified as targets. Other studies using matching have alleviated these problems of equal-sized samples by using either ratio matching (Stuart, 2010) or natural proportions of target and non-target mixes. Ratio matching refers to using a specific coefficient of how many times more non-targets there should be in the sample relative to targets. Previous research has at least used ratios of two (Dietrich & Sorensen, 1984) and three (Espahbodi & Espahbodi, 2003). The problem is that the ratio is generally selected arbitrarily and the distributions of targets and non-targets does not necessarily reflect the reality. In the natural proportion approach (eg. Walter, 1994; Brar et al., 2009; De & Jindra, 2012), researchers use the natural distribution of the targets and non-targets and match the samples without eliminating a significant number of non-target observations (as the case was with equal-sized and ratio matching). The ratio-based sampling does not bias the distribution between targets and non-targets leading to more robust findings (Brar et al., 2009). A general pitfall with the matched samples methods in the past research has been the consideration of only firms that have data during the entire time period (eg. Palepu, 1986; Brar et al., 2009), thus creating survivorship bias in the study.

The previous research has generally used four different criteria/variables for matching: random matching, size, industry and year. In random matching, the targets are matched with randomly selected non-targets and this method was used at least by Wansley et al. (1983), Palepu (1986), Walter (1994) and Powell (1997). For example, Palepu (1986) simply included every 6th non-target firm from the dataset to have equal-sized target and non-target samples. Many studies have used a single matching variable of size (Stevens, 1973), industry (Dietrich & Sorensen, 1984) or year (Brar et al., 2009), or they have combined two or more of the previous variables (Espahbodi & Espahbodi, 2003; Ouzounis et al., 2009). On top of the four standard matching criteria, Brar et al. (2009) employed a secondary matching method for robustness, where they matched with undervaluation and stock price momentum.

During the modern era, the sampling method has shifted towards panel data sampling, where the sample is constructed as panel data using firm-years rather than firms as used with the matching approach. These studies include, for example, Cremers et al. (2009), Cornett et al. (2010), Bhanot et al. (2010), Edmans et al. (2012) and Danbolt et al. (2016). In the panel data approach, a single firm contributes as many firm-year observations to the data set as it has been alive during the measurement period. This approach allows researchers to include both dead and alive firms to avoid survivorship bias (Tunyi et al., 2019). Sample sizes are larger when using firm-years; for instance, in Tunyi et al.'s (2019) research the sample consisted of nearly 40,000 firm-year observations from 3522 firms. The studies using panel data sampling utilize the entire dataset from the observed years without leaving out any non-targets (as a pursuit to balance the ratio between targets and non-targets). This is in line with, for example, Bartley and Broadman's (1990) critique regarding equal-sized target and non-target samples.

In this study, the panel data sampling is combined with matching - the sample is constructed in firm-years to increase the number of observations while various matching approaches are applied to improve the comparability between targets and non-targets. Most of the previous studies using matching have not explicitly disclosed the matching methodology and none of the studies have used more sophisticated matching methods, which this study will explore more in-depth. Matching is presented more extensively in section 2.5.

Holdout sample

Holdout samples were discussed above in the train-test split section from the perspective of splitting the entire dataset into train and holdout samples. In that section, the holdout period lengths used in the previous studies were also introduced. Here the focus is on the composition of the holdout sample itself. During the pre-Palepu period, studies generally used equal proportions of targets and non-targets in the holdout sample for prediction estimates (e.g. Stevens, 1973; Wansley et al., 1983). Instead of equal proportions, some researchers pushed up the number of non-targets in an arbitrary fashion. This meant including, for example, two times more non-targets relative to targets (Dietrich & Sorensen, 1984) or setting the number of non-targets to 200 versus 38 targets (Espahbodi & Espahbodi, 2003). One of the three main points of critique in Palepu's (1986) renowned study was directed towards the use of non-random holdout samples. He stated that there is no econometric justification for employing non-random samples for prediction tests, and prediction inferences can not directly be generalized to the population with non-random holdout samples. As the rare-event problem of takeovers makes predicting them "like searching for a needle in a haystack" (Palepu, p.10, 1986), the more balanced distribution of targets and non-targets underemphasizes the issue. In order to avoid the bias, he suggested using a random holdout sample resembling the entire population as closely as possible or even using the entire population.

Most of the studies after the Palepu's paper indeed followed the critique. Generally, the research that used a one-year holdout period employed all of the targets and non-targets available during that year (e.g. Powell, 2004; Ouzounis et al., 2009). On the other hand, Brar et al. (2009) set randomly 50% of the targets and non-targets aside each year as a holdout sample. They used the natural proportions of targets and non-targets from the start, and thus, the holdout sample represented the random sample representing the entire population in line with Palepu's (1986) critique. This thesis follows the current approach based on Palepu's (1986) critique and uses a multi-year holdout sample consisting of all targets and non-targets.

2.4.3 Prediction: methods for classifying targets and non-targets

In this subsection, the important methodological choice of classifying firms into targets and non-targets post takeover likelihood determination is discussed. After the parametric quantitative model has provided takeover likelihoods between 0 and 1 for the predicted firm, the firm still has to be classified as either target or non-target (Palepu, 1986). The methods discussed here define the boundary for classifying the firm as a target or a non-target. These methods include cut-off probabilities and various fixed percentile selections.

Cut-off probabilities have been the traditional and most commonly used method for classifying targets and non-targets; it sets a specific value and if the takeover likelihood of the firm is above the cut-off probability, it is classified as a target and as a non-target otherwise. Similarly, with other methodological choices such as quantitative model and holdout sample, Palepu's (1986) critique on cut-off probabilities was influential for the following research in takeover prediction. Early studies in the research domain used arbitrary cut-off probabilities for the predictions, which were typically set to the middle, 0.5 (Palepu, 1986). As the previous studies did not define the decision context in which the prediction results would be used, the prediction findings were difficult to interpret and could not be compared to one another. Palepu (1986) argued that the decision context was important because it sets the baseline for defining the cut-off probabilities, which in turn defines the classification of targets and non-targets and, eventually, the prediction results. Following the critique, Palepu (1986) derived the optimal cut-off probability by minimizing the total number of misclassifications. The decision context in his paper was to maximize the expected payoff as an investor. Thus, his core assumption was that the cost of type 1 (a target incorrectly classified as a non-target) and type 2 errors (a non-target incorrectly classified as a target) are similar (Powell, 2004). Given the decision context of maximizing expected payoff, Powell (2004) criticized the assumption of equal costs for type 1 and type 2 errors since the penalty of misclassifying a target would exceed a non-target. This is due to gains to target firms largely exceed those to firms not taken over, and thus, missed gains of misclassifying a target would largely exceed the penalty of misclassifying a non-target. Powell (2004) derived his cut-off probability by maximizing the proportion of target firms among the predicted targets, i.e. maximizing the ratio of true positives to predicted positives (precision).

During the modern era, research has adopted an alternative method of using fixed percentiles to classify companies as targets and non-targets. With the percentile approach, a particular share of the firms with the highest takeover likelihood are classified as targets and the rest as non-targets. Previous research has set the limit to 10% (Brar et al., 2009; Cremers et al., 2009) or 20% (Danbolt et al., 2016). The use of fixed percentiles poses a challenge of how to determine the optimal percentage. Percentiles do not allow for yearly flexibility in the M&A activity and, for example, Harford's (2005) research shows that the takeover activity indeed varies between time periods. Due to the critique on the theoretical grounding of fixed percentiles and the wide use of cut-off probabilities, this study implements the cut-off probability approach.

2.5 Matching in previous literature

In section 2.4.2, matching was examined in the context of the important methodological choices employed in the prior research on takeover prediction. As it was discussed, matching is a widely used sampling method in the literature domain but has lacked transparency in the implementation. This section focuses solely on matching to provide a more holistic view of the topic. After defining matching, its advantages are discussed, the matching process is briefly presented and different types of matching techniques are examined.

2.5.1 Why matching?

Matching can be understood from two different definitions from previous literature that highlight different aspects of matching. "Matching is an increasingly popular method for preprocessing data to improve causal inferences in observational data" (King & Nielsen, p.1, 2019) and "we define "matching" broadly to be any method that aims to equate (or "balance") the distribution of covariates in the treated and control groups" (Stuart, p.2, 2010). In order to deconstruct the definitions, we will analyze matching from two sides.

Firstly, matching is a method for preprocessing the data (Ho et al., 2007). Following Stuart's (2010) logic, any study estimating effects and outcomes (for instance, how independent variable affects dependent variable in regression) can be considered consisting of two stages: (1) design and (2) outcome analysis. In stage 1, the non-randomized sample is preprocessed aimed to replicate a randomized experiment (more in-depth next paragraph). Matching is a key tool in this design stage (Stuart, 2010). After preprocessing the data with matching techniques, the outcome analysis for causal effects (stage 2) can be executed with any analysis method that would have been applied without matching (Ho et al., 2007), for example a regression analysis.

The second part of deconstructing the definition of matching is connected to its advantages: what matching improves and why. Understanding the constituents of takeover likelihood is an estimation of causal effects; the aim is to explain the effect on takeover likelihood if variables X, Y and Z change by certain amounts. In its core, the estimation of causal effects is a comparison of potential outcomes (Rubin, 1974), in particular, a comparison of the same observation when it receives treatment and when it does not receive treatment (Stuart, 2010). As in this hypothetical scenario the observations would be identical apart from the treatment, a 'pure' treatment effect could be measured. As Holland (1986) demonstrated, the fundamental problem in this estimation of the causal effect is our ability to observe only one outcome for each observation, as each observation either will or will not receive treatment, never both. Hence, in the case of takeover likelihood, the ideal situation would be to compare the characteristics of the same company at the same point in time as an individual entity and as having been acquired - naturally that is impossible. Rubin (1976) aptly described the estimation of the causal effect as a missing data problem. Considering the above, to estimate the unobserved potential outcomes and to make good-quality causal inferences, the treatment and control groups should be as similar as possible (Stuart, 2010). One could describe this as comparing apples to apples. This is where matching is advantageous because it indeed strives to make the treatment group and control group as similar as possible (Ho et al., 2007) by "...equating (or "balancing") the distribution of covariates in the treated and control groups" (Stuart, 2010, p.2). Hence, matching improves the causal inferences from observational data (King & Nielsen, 2019).

To state in other words, matching controls for confounding effects from the matched variables, thus reducing the imbalance between the treatment and control groups (King & Nielsen, 2019). Another perspective (from that in the previous paragraph) on reduced imbalance is that it decreases model dependence (Ho et al., 2007; Imai et al., 2008), which consequently, reduces researcher discretion and bias (King & Nielsen, 2019). To clarify this logic, with imbalanced treatment and control groups, there is more diversity of estimates that different analysis models produce. Thus, the researcher/analyst is left with two or more models that can generate largely different causal estimates while fitting the data nearly equally (King & Zeng, 2006). In the end, this uncertainty leads to a situation where the researcher has to choose to report one or, at the most, few of these possibly incoherent-but-equally-valid models in the publication (King & Nielsen, 2019). The diverse estimates in the presence of model dependence cause researchers to have indirect discretion to the results (through the model selection) they choose to publish, and that leads directly to bias (King & Nielsen, 2019). Rightfully, Ho et al. (2007, p.199) ask "How do readers know that publications are not merely demonstrations that it is *possible* to find a specification that fits the author's favorite hypothesis?".

2.5.2 Matching process and matching types

As introduced earlier, causal research could be divided into design and outcome analysis stages. The design stage can further be split into smaller substages: (1) determining the variables used in matching, (2) measuring distance between the observations to define the matches and (3) implementing a matching method based on the distance measure (Stuart, 2010). Matching types can be classified into two dimensions: distance measure and matching method. In this study, 'matching type' refers to the combination of the two. This section focuses on different distance measures and matching methods, and presents viewpoints from past literature. In methodology section 4.2, the technical details of the matching methods are presented.

Distance measures

Previous research has used three dominant distance measures for defining the matches (Stuart, 2010). These are exact matching, Mahalanobis distance and propensity scores. Exact matching is the simplest of the three and it matches the treatment and control units only with exactly the same values on all covariates (Ho et al., 2011). The requirement for the exact matches is both a key weakness and a strength of exact matching; while the exact matches should logically balance the treatment and control samples (Imai et al., 2008), in reality the strict requirement often results in many individuals not being matched consequently leading to a high number of pruned observations. Thus, the bias occurring as an outcome of the pruning may be larger than more imprecise matches with a higher number of individuals remaining in the analysis (Rosenbaum & Rubin, 1985). An advancement from the simple exact matching is coarsened exact matching (CEM) introduced by Iacus et al. (2012). The fundamental idea of CEM is to broaden the exact matching by coarsening, or splitting, each variable into intervals (e.g. instead of having age as years, CEM would use 0-30, 30-60 and >60 intervals). The exact matching algorithm is then applied to define the matches, thus pruning only the groups without observations from both treatment and control groups (Iacus et al., 2012). CEM should lead to less pruned observations, and therefore, overcome a key complication of exact matching.

With more than two covariates, the observation space becomes multidimensional. Mahalanobis distance (MD) is a widely-used distance measure in a multidimensional space with a variety of use cases also on top of matching. Prior literature has found MD to perform relatively well with few matched covariates, fewer than 8 (Rubin, 1979), but to perform worse than propensity scores with many covariates (Gu & Rosenbaum, 1993). Stuart (2010) suggested that this might be due to MD overmatching with multiple dimensions.

The most popular of all distance measures is propensity score matching (PSM) (King & Nielsen, 2019), which was considered a major advancement at the time of the introduction by Rosenbaum and Rubin (1983). The wide adoption of PSM is also confirmed by a Google Scholar search; PSM yielded over 107,000 results while exact matching and MD matching generated 48,400 and 32,200, respectively[1]. PSM is an intuitive method as it removes the multidimensional aspect by condensing all of the covariates into one single variable - the probability of receiving treatment (Stuart, 2010). The simplicity and strong endorsement of PSM from prominent researchers in various fields are likely to be key reasons behind its popularity (Pearl, 2010).

Despite PSM being the most broadly used matching method and even described as the most developed strategy for studying causal effects (Pearl, 2010), recently King and Nielsen (2019) published a widely-recognized[2] research paper criticizing PSM and suggested replacing it with alternative distance measures. Their critique was based on the inherent property of PSM that it approximates a completely randomized experiment. In contrast, the other two distance measures mentioned above aim for a fully blocked randomized experiment. The goal for the both types of experiments is to balance the distribution of the covariates - on both observed covariates (that are measured and used as matching criteria) and unobserved covariates (that might have been unknown or simply were not measured). Complete randomization balances, on average, both observed and unobserved variables. Fully blocked randomization improves this by exactly equating the observed variables and still, on average, balancing the unobserved variables. PSM's quest for complete randomization, and thus, the averaged-balancing of covariates leads to random pruning of observations. This difference is pivotal since, the distance between the observations likely increases with random pruning, consequently increasing the imbalance between treatment and control groups and leading to higher model dependence, researcher discretion, bias and lower-quality causal estimates (King & Nielsen, 2019).

A direct response to King and Nielsen's research was proposed by Jann (2017)[3][4] in an industry event, where he argued that PSM only partially approximates complete randomization; to be exact, PSM approximates it only within observations with the same propensity score. Hence, this would put PSM to somewhere between complete randomization and fully blocked randomization (Jann, 2017).

Matching methods

Matching methods use the distance measure to execute the matching and they primarily differ in how many observations are pruned and in the weights that remaining observations receive (Stuart, 2010). These methods do not apply to exact matching measures as they only match treated and controlled observations with the same covariate values. Matching methods include at least nearest neighbor matching, subclassification and full matching. Nearest neighbor is one of the most common matching methods, the easiest to understand and most

[1] Google Scholar search on 26/03/2020 with search terms "propensity score matching", "exact matching", and "mahalanobis distance" AND "matching"

[2] 469 citations as of 26/03/2020

[3] King and Nielsen's (2019) paper was originally published in 2016. Thus, response already from 2017.

[4] Ben Jann is a professor in University of Bern.

straight-forward to implement (Rubin, 1973). It simply matches the treated observation and the control observation with the smallest distance in between. Nearest neighbor can be implemented in various ways including 1:1 matching, ratio matching (multiple control observations matched with a treated observation) and using caliper (the matching is executed only if the distance is within pre-specified distance) (Stuart, 2010). 1:1 matching has been criticized in pure matching literature and in takeover prediction literature of pruning a large amount of observations, thus leading to reduced power (Stuart, 2010) and biased estimates (Bartley & Boardman, 1990). On the other hand, ratio matching has received critique on the decreased quality of matches as the observations are further away from each other (Stuart, 2010). Gu and Rosenbaum (1993) found the use of calipers outperforming methods without them.

Unlike matching individual observations as in the nearest neighbor method, subclassification forms groups from similar observations defined by for example quintiles (Stuart, 2010), and then directly compares only treated and control units within the same subclass (Rosenbaum & Rubin, 1984). The aim is to equate the distribution of the covariates within the subclasses while the distribution may be very different across the subclasses (Ho et al., 2007). Subclassification requires a single distance measure for the observations to create the subclasses, thus only PSM can be used from the ones introduced above (i.e. not the multidimensional MD) (Stuart, 2010). Full matching is a more sophisticated alternative for subclassification as the number of treated and control observations can vary across the subclasses, although always including at least one of each, and it automatically selects the number of subclasses (Hansen, 2004; Stuart & Green, 2008). Full matching optimizes these by minimizing the average of distances between each treated and control observation within each subclass (Stuart, 2010; Ho et al., 2011). Subclassification does not provide this degree of flexibility by requiring to define both of these ex-ante (Ho et al., 2007; Ho et al., 2011).

Choosing between methods to implement

The challenge with the wide variety of both distance measures and matching methods is that there is relatively little guidance for appropriately choosing between them (Stuart, 2010). For distance measures, prior research has found varying results in studies comparing them and there is not coherence on the theoretical grounding of the measures (e.g. King and Nielsen's (2019) critique on the most popular distance method PSM). Generally, the advice for selecting between matching methods has been to pick the method resulting in the best covariate balance (Ho et al., 2007; Rubin, 2007). Also as Stuart (2010) described, the matching research has been dispersed across various disciplines such as statistics, political science and accounting without a combined effort to define best practices. For instance, Shipman et al. (2016) showed that PSM had become a widely-used technique in accounting literature but studies often had theoretical shortcomings and failed to disclose important design choices. Similarly, matching has been used quite broadly in takeover prediction research but studies have often neglected the transparency regarding the design choices. Therefore, this study strives to (1) compare various matching types to determine the impact and consequence of choosing one, and (2) to be transparent on the design choices regarding matching and encouraging the future research to do the same for better replicability and comparison of the results and studies.

From distance measures, CEM, MD and PSM are implemented in this study. Exact matching was excluded as CEM was considered an advancement. From matching methods, 1:1 nearest neighbor with calipers and full matching are executed. Despite the critique, 1:1 nearest neighbor was selected since equal-sized training samples were previously the standard in the influential literature on takeover predictions (e.g. Palepu, 1986). The inclusion of 1:1 matching provides an interesting benchmark for the other methods. Calipers were added due to positive prior findings (Gu & Rosenbaum, 1993). Subclassification was left out due to full matching is also considered to be an improvement.

3. Hypotheses and matching variables

Chapter three focuses on developing the hypotheses and introducing the matching variables. Section 3.1 develops the hypotheses used in the outcome analysis as independent variables for the regression model. These hypotheses are expected to have an impact on the takeover likelihood. Additionally, the variables used in matching are developed and motivated in section 3.2. These are aimed at improving the comparability and causal inferences between targets and non-targets.

3.1 Hypotheses development

The objective of takeover hypothesis development is to search for and identify firm characteristics that either increase or decrease their likelihood of becoming takeover targets. As covered in the literature review section 2.3, many researchers have attempted to identify the combination of variables possessing the greatest discriminatory ability for distinguishing targets from non-targets. Some researchers have relied on arbitrarily chosen variables, while others required them to have theoretical justification. Palepu (1986) was the first to develop hypotheses inferred by academic literature, where many of his propositions received a wide adoption in the takeover likelihood field. The most widely adopted hypotheses developed by him were (1) Inefficient management, (2) firm size, (3) firm undervaluation and (4) growth-resource mismatch. Although some of the variables used to proxy for these hypotheses had been suggested prior to Palepu's study, they became the norm after the publication of his paper. Since then, two new hypotheses have received broad adoption, namely tangible assets hypothesis by Ambrose and Megginson (1992) and free cash flow hypothesis by Powell (1997). These six hypotheses are included in this thesis. Additionally, a revised firm size hypothesis is proposed and two new hypotheses of industry concentration and share repurchase are developed with support from prominent financial literature.

The structure of this section is as follows: management inefficiency (3.1.1), firm size (3.1.2), revised firm size (3.1.3), undervaluation (3.1.4), growth-resource mismatch (3.1.5), tangible assets (3.1.6), free cash flow (3.1.7), industry concentration (3.1.8) and share repurchase (3.1.9).

3.1.1 Management inefficiency

Management inefficiency is one of the most recognised theories behind mergers and acquisitions (see e.g. Manne, 1965; Jensen & Ruback, 1983; Jensen, 1988; Morck et al.,1989). This has perhaps been the reason for its wide adoption in the takeover likelihood modelling field after it was proposed by Palpeu (1986) as one of the main hypotheses for takeover prediction. The hypothesis builds on the theory that underperforming management will attract competition from more efficient management seeking to create superior value for investors through better use of firm resources. Acquisitions are thereby only a mechanism by which the incumbent management team is replaced by a new one. The hypothesis builds on the market for corporate control (MCC) theory and agency theory.

The market for corporate control has long been recognized as a motive for acquisitions (see e.g. Manne, 1965), but it was not until Jensen and Ruback's (1983) review of the scientific evidence that it received wide adoption. The theory states that shareholders lack loyalty to any management team as they only care to maximize their holdings' dollar value. Thus, shareholders allow control to the party, which offers them the greatest monetary value by either selling their holdings at the market price, replacing the current management team or allowing the existing executives continued control over the firm (Jeansen & Ruback, 1983). This means that different management teams compete for the opportunity to manage the firm, thus making the corporate world more efficient as underperforming management is replaced by more competent teams (Manne, 1965).

Management inefficiency can be measured with the underperformance of targets prior to the acquisition. Although there is a tendency that management teams are replaced in situations where firms are acquired (Brealey et al., 2017), the literature has been inconsistent in establishing whether targets tend to underperform prior to acquisitions or not. When assessing the short term returns in the period prior to the acquisition, researchers find that targets earn either positive abnormal return (Dodd & Ruback, 1977) or insignificantly different from zero (Mandelker, 1974; Langetieg, 1978). This finding has been contradicted by evidence from Asquith (1983), who found that targets on average earned -14,8% between day -480 and day -60 prior to takeover announcement. The perhaps most compelling evidence was generated by Grossman and Hart (1980), Jensen (1988) and Morck et al. (1988) who prove that shareholders of acquired firms tend to benefit from acquisitions based on evidence from the takeover market.

This trend of inconclusive results is further repeated in the takeover likelihood literature, where some studies find that takeover targets are characterized by having poorer accounting profitability (e.g. Barnes, 1999; Pasiouras, 2007; Ouzinis et al., 2009) and market performance (Powell & Yawson, 2007). Other studies find the opposite relationship where targets are characterized by superior accounting performance (Brar et al., 2009) and market-based performance (Palepu, 1986), while a third group of studies finds no significant difference at all (e.g. Ambrose & Megginson, 1992; Powell, 1997).

The wide adoption of the hypothesis in combination with the variety of proxies used to measure it indicate an agreement regarding its validity, but also a lack of consensus regarding what constitutes poor managerial performance. The used proxies can be divided into two groups of accounting and market-based financial ratios. For the accounting based proxies measuring firm performance, the most frequent ones have been return on assets (ROA), return on sales and operating profit margins (e.g. Ambrose & Megginson, 1992; Barnes, 1999; Pasiouras et al., 2007; Ouzounis et al., 2009), while the market performance usually relies on some form of stock return (e.g. Powell & Yawson, 2007). The major difference between these groups is that the accounting ratios are based on historical performance and are considered lacking the ability to reflect future consequences of current managerial actions (Rappaport, 1986). On the contrary, market-based ratios build on the assumption that the current firm value represents the present value of future cash flows, which consequently, result from the future actions of the current management (Lambert & Larcker, 1987). As the two groups of ratios measure aspects of managerial actions (past and future), they can be seen as complementary to offer a broader representation of managerial capabilities. Following previous research, the hypothesis of inefficient management is, therefore, tested by investigating both accounting profitability and stock market performance. In line with Palepu (1986), the hypotheses are as follows:

Hypothesis 1: Ceteris paribus, the likelihood of a firm becoming a takeover target is inversely related to its performance.

Following the example set in previous literature both an accounting (historical) and market (future) measure were employed to measure the two dimensions of management performance.

The historical measure performance is in line with Palepu (1986) and is proxied by return on capital employed (ROCE). ROCE measures how efficiently management utilizes the resources in generating profits through its operations. It is calculated as the ratio of EBITDA [WC01250] to total capital employed [WC03998].

$$ROCE = \frac{EBITDA}{Total\ Capital\ Employed} \tag{1}$$

The market measure is proxied by the one year stock return measured in the growth of the share price P [UP] between period $t-1$ and t. The formula is as follows:

$$Stock\ return = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{2}$$

3.1.2 Firm size

The firm size hypothesis is one of the most consistently used hypotheses across all eras. Palepu (1986) suggested that the relationship between takeover likelihood and firm size is inverse, where smaller firms are more likely to become targets. The theoretical foundation predominantly builds on the assumption that there are multiple firm size-related transaction costs (e.g. takeover premium and cost of absorbing and integrating the target) associated with an acquisition (Powell, 2001). This indicates that as these costs increase, the number of firms who can afford to acquire the target decreases (Palepu, 1986; Gorton et al., 2009). This affordability argument, powered by transaction cost theory, therefore lies at the center of this hypothesis.

The empirical evidence is, to some extent, inconclusive as the hypothesis is not consistently significant in all studies. For instance, Ambrose and Megginson (1992) and Powell (1997) fail to validate the hypothesis when distinguishing between friendly and hostile takeovers, and testing its robustness across time. The assumed negative relationship between size and takeover likelihood was also questioned by the merger wave literature. Hughes (1987), Mitchell and Mulherin (1996) and Harford (2005) noticed that the targets tended to be larger in size with certain acquisition motives. On the other hand, studies with similar sampling methodology to Palepu (1986) have managed to generate a significant result for the hypothesized negative relationship between size and takeover likelihood (e.g. Hasbrouck, 1985; Powell, 1997; Barnes, 1998; Powell, 2001). This hypothesis follows the original proposal of Palepu (1986):

Hypothesis 2: Ceteris paribus, takeover probability decreases with firm size

Several proxies have been used to account for firm size while the most adopted has been the natural logarithm of total assets (e.g. Powell, 1997; Powell and Yawson, 2007; Cornett et al., 2011). This proxy is considered better at accounting for the various size-related transaction costs compared to the alternative proxy of net book value proposed by Palepu (1986). This has to do with the latter proxy's inability to distinguish between highly levered firms with high total assets from firms with low debt and low total assets. Therefore, this paper will rely on the natural logarithm of total assets [WC02999].

$$Firm\ size = \ln\ (Total\ assets) \tag{3}$$

3.1.3 Revised firm size

In the previous section, it was argued that takeover likelihood and firm size have a negative linear relationship, where smaller firms are expected to be associated with a higher takeover likelihood. When additional theories and motives behind acquisition are introduced, the previously hypothesized relationship is not supported. In fact, many of these theories suggest that bidding firms would be more interested in acquiring relatively larger firms. Additionally, assuming that Gibrat's laws[5] regarding firm size distribution holds, the relationship

[5] Gibrat's law assumes that firm size is approximately lognormally distributed, see Angelini and Generale (2008) for more information. Gibrat's law is also known as the law of proportionate effects (Sutton, 1997).

becomes concave. This indicates that initially there is a positive relationship between firm size and takeover likelihood. After passing a specific threshold, the relationship is flipped as takeover likelihood decreases with firm size. That is due to increased transaction costs and a decreasing number of larger firms with required resources for the takeover. The concave relationship entails that the most likely targets ought to be mid-sized firms, all else equal.

As indicated, different merger theories anticipate varying relationships between firm size and takeover likelihood. Some of them, e.g. managerial utility maximization and empire-building, can directly explain the concave relationship while other theories are strictly associated with either a negative or positive relationship. To facilitate the discussion, these theories are divided into three groups. The first group A covers the theories explaining the concave relationship directly, group B presents the theories indicating a positive relationship while the last group C covers the theories with a negative relationship

The perhaps most important theory of group A is the managerial utility maximization theory. It stipulates that the reason managers engage in M&A activity is to increase their own utility (Marris, 1963; Mueller, 1969). However, it is unlikely that they will maximize their own utility if completely disregarding the utility of their shareholders. Jensen and Meckling (1979), therefore, argue that a more plausible explanation of the managerial utility theory is that managers pursue a shareholder wealth satisficing objective rather than wealth maximizing one. Thus, management is likely to engage in takeover activities, which allow them to increase their own utility, but do not directly harm shareholders' wealth creation. Consistent with the adapted version of managerial utility maximization theory, it can be observed that bidding firms do not profit from acquisitions and may even on occasion earn negative abnormal returns (see Jensen & Ruback, 1983; Higson & Elliot, 1998). This proves that acquisitions might, on average, be motivated by managerial self-interest (Malatesta, 1983). Several hypotheses have emerged from this theory. One of the most cited is the hubris hypothesis, which aims at explaining why managers tend to overspend on targets (Hayward & Hambrick, 1997). Another widely-recognized theory is empire-building, which suggests managers engaging in acquisitions to increase their own firm size, and thus, receiving additional remuneration and social status (Marris, 1963). Not all theories propose that acquisitions are conducted at the expense of shareholders. The monopoly theory advocates that a firm can increase its market power with the help of acquisitions and generate additional profits at the expense of industry competition and customers by charging higher prices (Eckbo, 1992).

The main argument for theories in group B (takeover likelihood increases with firm size) is that the acquisition of smaller targets is inconsistent with the neoclassical[6] and managerial utility motives of acquisition. Palepu (1986) and Gorton et al. (2009) argue acquirers being more likely to target smaller firms to minimize transaction costs. However, they fail to consider potential value creation motives as they can be argued to be

[6] Neoclassical merger motives state that managers aim to maximize firm value and engage in merger activity to increase market power or efficiency (Gorton et al., 2009)

directly associated with firm size (e.g. economies of scale and scope) (Gorton et al., 2009). A similar argument can be held for firms aiming to gain monopoly powers, or empire-building, as in those cases, it would be more attractive to target relatively larger firms. Additionally, the importance of M&A advisers should not be underestimated as they participate in most sales and might impact selecting the takeover target. Walter et al. (2008) show that these advisers have consistently tended to recommend larger acquisition targets as their reputation and revenue is directly associated with the value of their deal portfolio. On top of this, Pettit and Singer (1985) argue that smaller firms experience higher information asymmetry from potential buyers due to the lack of economies of scale in information production and distribution. This information asymmetry can cause a bidder to decline the possibility of acquiring a small firm due to the lack of insights and risk of purchasing a "lemon".

The motivation for group C has been covered more extensively in section 3.1.2. The hypothesis assumes that takeover likelihood is inversely related to firm size and was used by Palepu (1986), Walter (1994) and Powell (2001) among others. The main reason is the extra risk associated with higher transaction cost as larger firms are more difficult to finance and/or more challenging to integrate post-acquisition. Combined with Gibrat's law, it provides a solid explanation to why larger firms are less likely to become targets.

The combination of these three groups of theories helps to explain the concave relationship. The updated size hypothesis is therefore as follows:

Hypothesis 3: Takeover likelihood is a concave function of firm size.

To test the revised firm size hypothesis, a piecewise regression was conducted, where all observations were divided into five quintiles based on firm size. In each quantile, a logit regression was employed to evaluate the sign and significance of the coefficient. If there is a significantly positive (negative) relationship between the smallest (largest) firm size quintile and a reasonable coefficient for quintile two-four showing a convex relationship, the hypothesis will be considered significant. The methodology is covered more in-depth in section 4.3.5.

If the hypothesis is significant, it is included in the multivariate regressions by complementing the proxy of the old hypothesis (the natural logarithm of total assets [WC02999]) with the natural logarithm of total assets [WC02999] squared. The non-polynomial term is expected to have a positive relationship with takeover likelihood (representing smaller firms) while the added polynomial term is expected to have a negative coefficient (representing larger firms due to polynomial term).

3.1.4 Undervaluation

The valuation theory assumes that acquisitions are performed by bidding firms, who hold private information about the fundamental value of the target firm or have unique information regarding value creation via synergies (Trautwein, 1990). The misvaluation hypothesis builds on this theory arguing that stock markets are inefficient, and thus firms can be misvalued. Rational managers try to take advantage of these misvaluations by aiming to profit from them, thereby directly impacting the takeover activity (Shleifer & Vishny, 2003). Dong et al. (2006) argue that such takeover activity will occur when a target is either (1) undervalued and can be acquired for less than its fundamental value with a cash bid, or (2) if the target is overvalued, although less so than the bidder, and can be acquired with equity.

Although the misvaluation hypothesis specifies two cases where a firm can arbitrarily profit by acquiring mispriced firms, the takeover literature has mainly focused on (1) identifying undervalued firms. The motivation partly lies in that (2) overvalued firms are unlikely to be attractive takeover targets to the average acquirer as it is unlikely for them to be relatively more overvalued (Belkaoui, 1978). The undervaluation, instead of misvaluation hypothesis, therefore, suggests that undervalued firms are more likely to become acquisition targets to the average bidders. Hasbrouck (1985) noted early that firm undervaluation could arise from managerial inefficiency as a mismanaged firm often tends to fail reaching its true potential value. Researchers such as Palepu (1986), Morck et al. (1988), Martin and McConnell (1991) and Powell (1997) have shown that firm undervaluation is directly associated with takeover likelihood, while Walter (1994) finds that it is the most important hypothesis. In line with Palepu (1986) and other literature, the hypothesis is as follows.

Hypothesis 4: Ceteris paribus, takeover likelihood is directly associated with the level of firm undervaluation

The most consistently employed proxy to test the undervaluation hypothesis is the market to book ratio used by prominent researchers such as Palepu (1986), Ambrose and Megginson (1992), Powell (1997;2001), Dong et al. (2006) and Brar et al. (2009). Espahbodi and Espahbodi (2003) argue that if the value of a target's individual parts (book value) is greater than its current market value, its takeover likelihood should increase. The motivation is that the acquiring firm could either strip the parts of the target and sell them for a substantial profit, or alternatively use the target firm's assets to expand its own business. Following Palepu (1986), the market to book ratio is calculated as the market value of equity ([NOSH] * [UP]) to the book value of equity ([WC03501]-[WC02649]).

$$MTB = \frac{Book\ value\ of\ Equity}{Market\ value\ of\ Equity} \tag{4}$$

It is worth mentioning that the market to book ratio is not a pure firm undervaluation measure as it measures a combination of management inefficiency and firm growth opportunities (Hasbrouck, 1985; Espahbodi & Espahbodi, 2003).

3.1.5 Growth-resource mismatch

Neoclassical merger motives state that managers aim to maximize firm value and engage in merger activity to increase market power or efficiency (Gorton et al., 2009). This can be achieved through synergies such as economies of scale and scope, better use of resources and elimination of redundancies. Devos et al. (2009) identify three sources of value creation, which can arise from mergers, namely (1) financial synergies, (2) operational synergies and (3) the increase in market power. Devos et al. find that mergers, on average, create synergies equivalent to 10% of the combined equity value of the acquirer and target firm, where 81% (17%) of the total value creation can be prescribed to operational (financial) synergies. This view has much in common with the management inefficiency hypothesis and stipulates that through better planning and utilization of resources, the firm can increase shareholder wealth (Trautwein, 1990).

The growth-resource mismatch hypothesis is based on neoclassical merger motives where synergies can be created through complementarities (Manne, 1965; Trautwein, 1990). The hypothesis states that a growth-resource mismatch occurs when a rapidly growing firm faces financial constraints making it unable to finance profitable investments. This means that the firm in question has positive net present value investments but lacks the liquid assets, or capacity to raise additional debt, to finance these investments. Thus, a synergy can be created when a resource-rich counterparty acquires the firm and corrects the mismatch. If the opposite growth-resource mismatch (i.e. low growth and resource-rich) occurs, the firm has three options, (1) to retire any outstanding debt, (2) distribute the excess cash to shareholders or (3) acquire another firm, preferably one with the opposite growth resource mismatch (Palepu, 1981). Although the growth-resource mismatch has valid theoretical support, the empirical findings in takeover likelihood literature question its usefulness and validity (e.g. Ambrose & Megginson, 1992; Powell, 2004; Danbolt et al., 2016).

Palepu (1986) found the growth resource mismatch hypothesis significantly differing between target and non-target firms. In accordance, the hypothesis is stated as follows:

Hypothesis 5: Ceteris paribus, firms with a growth-resource mismatch are more likely to become targets.

This study replicated the approach to measure growth-resource mismatch with a dummy variable proposed by Palepu (1986). To calculate the growth-resource mismatch hypothesis three variables were relied: (1) sales growth [WC01001], (2) liquidity proxied by the ratio of cash and short term investments [WC02001] to total assets [WC02999] and (3) leverage proxied by debt [WC032559] to equity [WC03995]. When a firm has either of the two combinations of sales, liquidity and leverage represented in table 3.1.5, it is considered having a growth-resource mismatch and thereby assigned 1 and 0 otherwise. In accordance with Palepu (1986), the values for each of these variables are subsequently compared to the industry average meaning that it receives the value high (low) if it is higher (lower) than said average.

Table 3.1.5 – Growth-resource mismatch combinations

	Growth in sales	Liquidity	Leverage
High growth-resource poor	High	Low	High
Low growth-resource rich	Low	High	Low

Notes: This table presents the two possible growth resource mismatch combinations. Growth in sales represents the one year growth in sales. Liquidity represents the ratio between cash and short term investments to total assets. Leverage represents the debt to equity ratio. A high value indicates that the observed value is higher than the industry average. A low values indicates that the observed value is lower than the industry average.

Ideally, the forecast of a firm's future growth should be used for accurate results but considering the lack of valid estimates, the historical estimate was employed. The growth in sales [WC01001] for year t was calculated according to the following equation.

$$Sales\ growth_t = \frac{Sales_t - Sales_{t-1}}{Sales_{t-1}} \tag{5}$$

Sales growth was measured over a single year due to the adopted panel data approach. With panel data each firm year attributes one observation to the sample, thus making it impossible to use multiyear values.

3.1.6 Tangible assets

The financial literature has long been filled with studies investigating the impact of a firm's assets structure to its financial policy and decision making (e.g. Scott, 1977; Myers & Majluf, 1984; Bradley et al., 1984; Stulz & Johnson, 1985). There is a consensus that tangible assets provide firms financial slack as they can be used as collateral enabling them to raise debt capital when needed rather than solely relying on their shareholders (Myers & Majluf, 1984). Therefore, the level of tangible assets can be seen as a proxy for a firm's total debt capacity (Ambrose & Megginson, 1992). Stulz and Johnson (1985) argued that the debt capacity provided by the tangible assets could be the difference between a firm pursuing profitable investment projects or not.

Applying these findings to the takeover literature, it can be argued that firms with a high ratio of tangible assets could be seen as more attractive targets. This is because the acquirer can use the target's assets as collateral to raise parts of the funds needed to finance the takeover. That is, to some extent, in line with the corporate raider theory of takeovers as raiders tend to prefer targets with a higher tangible asset ratio (Eddey, 1991). Additionally, the presence of a high tangible assets ratio reduces uncertainty regarding the true value of a firm as they are easier to value than intangible assets such as brand, R&D and goodwill. However, that is against the undervaluation hypothesis as firms with a high asset concentration are unlikely to be substantially undervalued.

The takeover literature has found some empirical evidence in favor of the asset structure hypothesis. Ambrose and Megginson (1992) and Powell (1997) are two studies that find support for the tangible asset ratio being positively correlated with takeover likelihood. Ambrose and Megginson (1992) first introduced the hypothesis to the takeover prediction literature, although other studies have theoretically argued its potential prior to that (see Ambrose, 1990; Eddey, 1991). The hypothesis follows the proposal by Ambrose and Megginson (1992) and is:

Hypothesis 6: Ceteris paribus, takeover likelihood is positively correlated with the ratio of tangible assets to total assets.

The proxy used to test this hypothesis is similar to the one used by Ambrose and Megginson (1992) and Powell (1997). It is calculated as the ratio of property, plant and equipment [WC02501] to total assets [WC02999].

$$Tangible\ asset\ ratio = \frac{Property, Plant\ and\ Equipment}{Total\ assets} \tag{6}$$

3.1.7 Free cash flow

The definition of free cash flow is all cash flow generated by a firm in excess of what is required to finance all projects with a positive net present value (Jensen, 1986). To reduce agency costs and managerial misconduct, Jensen (1986) advocates that all excess free cash flow be paid out to the shareholders if the firm is to remain efficient. If free cash flow remains in the firm, the agency theory suggests that managers will engage in value destructive behavior such as increased managerial compensation and empire-building. These activities of managerial inefficiency raise attention to the market for corporate control (Manne, 1965; Powell, 1997) and can lead to firm undervaluation, thus increasing the firm's takeover likelihood (Jensen, 1986).

The hypothesis was first introduced to the takeover likelihood literature by Powell (1997) and became widely adopted after that. The empirical evidence has, however, been inconsistent as Powell (1997), Espahbodi and Espahbodi (2003) and Danbolt et al. (2016) managed to find a significant difference between targets and non-targets while Powell and Yawson (2007) and Brar et al. (2009) did not. However, no study has found a negative relationship between free cash flow and takeover likelihood. The hypothesis is as follows:

Hypothesis 7: Ceteris paribus, takeover likelihood is positively correlated with the level of free cash flow in the firm.

Consistent with Powell and Yawson (2007) and Danbolt et al. (2016), the proxy for takeover likelihood is calculated as the ratio of net cash flow from operating activities [WC04860] less capital expenditures [WC04601] to total assets [WC02999].

$$FCF = \frac{Net\ cash\ flow\ from\ operating\ activities - Capital\ expenditures}{Total\ assets} \tag{7}$$

The limitation of this proxy is that it fails to consider whether the capital expenditures are invested in positive net present value investments, or whether there are more positive net present value investments to be made.

3.1.8 Industry concentration

A concentrated industry is one with an oligopolistic industry structure and dominated by a few companies. This entails that a few firms control large market shares and consequently have substantial market power. These industries are often characterized by high entry barriers, high degree of customer loyalty, high switching costs, government policy to protect the industries, and intellectual property rights (Porter, 1979). Acquisitions in such industries can be limited due to antitrust regulations, which naturally reduces the takeover activity as industry concentration increases (Farrell & Shapiro, 1990).

The level of competition in high concentration industries generally tends to be lower as there are fewer participants. Many researchers have investigated the effect of industry concentration on the market for corporate control and agency problems in general (Holmström, 1999). The empirical evidence shows that industries characterized by low concentration (i.e. high competition) have a more active market for corporate control, which punishes and replaces inefficient management (Fama & Jensen, 1983; Shleifer & Vishny, 1997).

Industries characterized by low concentration should generally be associated with a higher takeover activity. A higher number of firms active in the industry lead to fiercer competition, thus increasing M&A activity. Additionally, antitrust regulation is a smaller threat. The industry concentration hypothesis is as follows:

Hypothesis 8: Ceteris paribus, a firm's takeover probability is inversely related to its industry concentration.

A common proxy for industry concentration is the Herfindahl-Hirschman index (HHI) and is used by studies such as Hou and Robinson (2006), Giroud and Mueller (2010) and Loderer et al. (2011). The index is computed as the sum of the squared market shares of all publicly traded firms in a specific industry. The market shares are estimated based on the ratio of a firm's [WC02001] to the sum of the total revenue ($\sum WC02001$) for all firms n in industry j during time t.

$$HHI_j = \sum_{i=1}^{n} \left(\frac{Rev_{it}}{\sum_{i=1}^{n} Rev_{it}} \right)^2 \tag{8}$$

A high value of HHI for industry j indicates a high industry concentration and vice versa.

3.1.9 Share repurchase

Share repurchase programs are a way of distributing excess cash flow to investors and have significantly increased in popularity over time (Billet & Xue, 2007), leading to relatively fewer firms paying dividends (Fama & French, 2001). The literature has investigated this trend and concluded that share repurchases play several roles such as distributing excess cash flow, signaling of firm undervaluation and firm capital structure readjustment (see e.g Harris & Raviv, 1988; Persons, 1994; Jagannathan et al., 2000; Dittmar, 2000; Grullon & Michaely, 2004; Brav et al., 2005; Billett & Xue, 2007)

Harris and Raviv (1998) hypothesized that share repurchase can be used as a defensive takeover mechanism. Firms can raise debt from the capital markets to finance repurchases of its own shares in an attempt to alter its capital structure. These repurchases further allow the firm to reduce the heterogeneous valuation among their shareholders. Bagwell (1991) explains that the shareholders who are willing to tender their shares, when a share repurchase offer is made, systematically have the lowest valuations. This means that repurchase programs eliminate shareholders with the lowest reservation values ultimately skewing the distribution of its shareholders towards a more expensive pool. This makes it more expensive for potential bidders to acquire the firm as they have to face the shareholders with a higher valuation. Harris and Raviv (1998) and Persons (1994) further argue that post a share repurchase program, the shares become relatively more concentrated among the friendlier institutional shareholders who are less likely to give way to a takeover by tendering their shares.

Fama and French (2001) find that share repurchases are used as a substitute for dividends indicating that they are used to distribute excess cash flows. This ought to reduce the agency problem similarly as dividends, and hence a firm's takeover likelihood. Coherently, Grullon and Michealy (2004) find that markets generally react positively to share repurchase announcements as they alleviate the agency problem by reducing excess cash flow. Therefore, it is expected that the presence of share repurchase contributes to a lower takeover likelihood. The hypothesis is as follows.

Hypothesis 9a: Ceteris paribus, takeover likelihood is inversely related to share repurchase

The literature regarding share repurchase programs and their impact on firm takeover likelihood is to some extent contradicting. Another perspective on the relationship between share repurchase and takeover likelihood stems from the information revealing hypothesis. The hypothesis suggests that share repurchases, just like dividends, signal the management’s private information about the firm's future prospects and that it is potentially undervalued (see e.g. Bhattacharya, 1979; Miller & Rock, 1985; Lakonishok & Vermaelen, 1990). The empirical evidence regarding market reaction is mixed; while few studies show that the market reacts positively to share repurchase announcements (Comment & Jarrell, 1991; Ikenberry et al., 1995; Peyer & Vermaelen, 2005), the majority suggest a systematic underreaction (Mitchell & Stafford, 2000; McNally & Smith, 2007; Yook, 2010).

The share repurchase hypothesis is, therefore, in line with the undervaluation hypothesis (see section 3.1.4), which suggests that undervalued firms are more likely to become targets. As the market consistently underreacts to share repurchase announcements, it indicates that prospective bidders can benefit from the markets’ systematic underreaction by targeting firms that announce share repurchase programs. The hypothesis is as follows:

Hypothesis 9b: Ceteris paribus, firms who engage in share repurchases are more likely to become takeover targets

These two hypotheses are contradicting but based on existing theories from financial literature. The results provided by including both hypotheses will shed light on which of these theories are better suited for the takeover likelihood literature. To measure the two hypotheses, a dummy variable was created to measure whether a firm had repurchased shares during the previous year. The variable was based on data from Thomson One database. A significant negative coefficient would support hypothesis A, while a significant positive coefficient would imply that hypothesis B is correct.

3.2 Matching variables

The section above established the takeover prediction hypotheses and presented their proxies. This section does the same for the variables used to match targets with non-targets in the training sample. Determination of variables follows Rubin (2001), who suggested that the variable selection for matching should be based on prior research and theoretical understanding.

Previous literature in takeover prediction has primarily matched with takeover year (e.g. Brar et al., 2009), industry (e.g. Dietrich & Sorensen, 1984) or both (e.g. Ouzounis et al., 2009). Matching by takeover year is generally motivated by aim to reduce the effects of economy-wide factors while the industry variable is included to eliminate industry-wide effects (Ouzounis et al., 2009; Espahbodi & Espahbodi, 2003). The present research complements the two variables with an estimation of bankruptcy risk. To the authors best of knowledge, risk of bankruptcy has not been used as a matching variable before in takeover prediction literature.

3.2.1 - Risk of bankruptcy

As mentioned in sampling section 2.4.2, a general pitfall in prior studies with matching approach is that they have introduced survivorship bias in their training samples by including only companies with data covering the entire period (e.g. Palepu, 1986; Ouzounis et al., 2009). Thus, the model does not experience data of bankrupt firms before testing, and consequently, the model is not trained to distinguish takeover targets from bankrupt companies. Commonly, the holdout dataset is not adjusted for bankruptcies and consists of all companies including to-be liquidated firms in the near future. On the other hand, the more recent research papers using panel data and including both surviving and bankrupt firms in the training sample have not controlled for the effect of bankruptcy leading to potentially inefficient parameter estimates, and therefore, higher errors in the prediction tests (Powell & Yawson, 2007).

The problem lies in that takeovers have similar characteristics to other restructuring events including bankruptcies. The variables selected for both takeover and bankruptcy models are typically based on the same theories relating to, for example, inefficient management, undervaluation, capital structure, growth-resource imbalances and industry structure (Powell & Yawson, 2007). Powell and Yawson (2007) find, for instance, that the likelihood for both takeovers and bankruptcies increase with lower stock market performance and growth, and with higher leverage and industry concentration. They raise concern for takeover prediction from the overlap of the shared characteristics between takeovers and bankruptcies. After all, many takeovers occur due to firms first being pushed to the edge of bankruptcy by high debt and poor performance and then rescued by the acquiring firm (Pastena & Ruland, 1986; and Clark & Ofek, 1994).

Powell and Yawson (2007) argue that the similarity between takeover targets and bankruptcies, and the isolated treatment with the two events in prior research are a significant cause for lowered prediction accuracy of takeovers. More specifically, this combination leads to high misclassification rates with many non-targets being falsely classified as targets (i.e. type 2 error). Due to the similar characteristics between targets and bankrupt firms and not having trained the model to distinguish between the two groups, many bankrupted firms wind up as these misclassified targets increasing the type 2 errors and lowering prediction accuracies (Powell & Yawson, 2007). For investors looking to profit from takeover prediction, type 2 errors have a special caveat; when a bankrupt firm is misclassified as a target, it ends up being invested in and will generate a profit of -100% driving down the portfolio profits heavily. Due to these and other poorly performing misclassified non-targets, type 2 errors have frequently been argued to explain the non-abnormal returns of takeover prediction portfolios (e.g. Palepu, 1986; Powell, 2004).

Considering the high type 2 errors in the previous research (Powell & Yawson, 2007), the important consequences of these errors (Palepu, 1986) and the need of controlling for bankruptcies to account for the type 2 error (Powell & Yawson, 2007), this study will use the risk of bankruptcy as a variable for matching. Accounting for bankruptcy risk as a matching variable allows comparing takeover targets to non-targets with equal or nearly equal likelihood of going bankrupt, thus training the model to distinguish between targets and to-be bankrupted firms.

Bankruptcy prediction models

Bankruptcy prediction models can be divided into three dominant approaches in the previous research: accounting information-based models, contingent claims-based models and hazard models (Bauer & Agarwal, 2014). Accounting-based models utilize publicly available information, mainly accounting ratios, and employ these to differentiate between liquidated and unliquidated firms. The procedure is a structured fundamental analysis of the company's financial situation (Bauer & Agarwal, 2014) aimed at distinguishing between to-be bankrupted and surviving firm characteristics. Accounting-based models include Altman's (1968) prominent z-score and a later improvement, Ohlson's (1980) O-score, which is implemented in the underlying study. Contingent claims models view equity as a call option on assets while newer hazard models assess bankruptcy risk using both accounting and market variables in a time-varying fashion (Bauer & Agarwal, 2014).

The findings in the previous literature are relatively incoherent with respect to the preferred approach for bankruptcy prediction. Prior research comparing accounting information-based models to the contingent claims models have found contingent claims models outperforming accounting models (Hillegeist et al., 2004), accounting models being better in the short-term but inferior in the long-term (Reisz & Perlich, 2007) and accounting models having slightly better accuracy but both models capturing significant information about the failure (Agarwal & Taffler, 2008). Studies including hazard models to the performance comparison have, although, generally found superior performance for hazard models over the others (e.g. Bauer & Agarwal, 2014; Campbell et al., 2008).

As accounting information-based models require less resources to implement and have still shown to perform well in predicting bankruptcies, this study will utilize them. Lower resource requirement springs from neither having to collect market data nor having to implement a regression model (hazard model) or normal density function (contingent claims model). Accounting-based model allows simply implementing a predefined linear combination of accounting ratios. The parameters for the accounting ratios are the best linear combination found in the research (Bauer & Agarwal, 2014). As previous research has considered Ohlson's O-score as an improvement to Altman's z-score and recommended using it as a preferred model (Begley et al., 1996), the former is chosen for this study. Literature has found the O-score model to outperform z-score both theoretically[7] and in empirical tests (Begley et al., 1996). The formula for the o-score is as follows:

$$\begin{aligned} O - score = &-1{,}32 - 0{,}407SIZE + 6{,}03TLTA - 1{,}43WCTA + 0{,}70757CLCA \\ &- 1{,}72OENEG - 2{,}37NITA - 1{,}83FUTL + 0{,}285INTWO - 0{,}521C \end{aligned} \tag{9}$$

,where $SIZE = \log \frac{Total\ assets}{GNP\ price{-}level\ index}$, $TLTA = \frac{Total\ liabilities}{Total\ assets}$, $WCTA = \frac{Working\ capital}{Total\ assets}$, $CLCA = \frac{Current\ liabilities}{Current\ assets}$, $OENEG = 1\ if\ total\ liabilities > 0, otherwise\ 0$, $NITA = \frac{Net\ income}{Total\ assets}$, $FUTL = \frac{Cashflow\ from\ operations}{Total\ liabilities}$, $INTWO = 1\ if\ net\ income < 0, otherwise\ 0$, $CHIN = \frac{NI_t - NI_{t-1}}{|\mathrm{NI_t}| + |\mathrm{NI_{t-1}}|}$ where NI is the net income.

It is acknowledged that hazard models with logit regression or even more advanced methods as suggested by Jones et al. (2017) might yield better results for calculating the risk of bankruptcy.

7 O-score is derived from a logit model analysis while z-score is based on multiple discriminant analysis (MDA). Logit model overcomes many of the statistical issues inherent in MDA (Begley et al., 1996). The improvement of the logit model compared to the discriminant analysis was discussed earlier in section 2.4.1 when comparing models used in takeover prediction.

4. Methodology and data

The methodology chapter introduces the data and the methodology employed in this thesis. First, the sample construction is discussed (4.1) followed by explanation of matching for data preprocessing (4.2). The approach for explanatory analysis is presented in 4.3 including methods for hypothesis validation and measurement of explanatory power. Finally, the methods for predictive analysis are discussed in 4.4.

4.1 Data

This section presents the data collection, sample construction(s) and the handling of outliers. The structure is as follows: 4.1.1 covers the training sample construction and retrieval of the independent variables, 4.1.2 covers the construction of the holdout sample, 4.1.3 discusses the retrieval of data regarding the dependent variable, and 4.1.4 explains the handling of outliers.

4.1.1 - Training Sample construction and independent variables

The first step in collecting the sample was to identify all publicly traded US firms that have been active for a minimum of one year at some point in time for the period of 2000-2013. This is achieved by relying on the Worldscope US constituents list(s) (Datastream code: WSUS*), which contains all American publicly traded firms filing with the Security Exchange Commission (Thomson Reuters, 2015). A total of 16 918 unique firms that fulfilled the requirements were identified and extracted together with their Datastream code, International Securities Identification Number (ISIN) number and basic company information. This Datastream code was used to retrieve the financial data needed to construct the proxies for the hypotheses developed in section 3.1. This data was structured in a panel data format consistent with approaches adopted by similar studies such as Cremers et al. (2009), Bhanot et al. (2010) and Cornett et al. (2011).

Having identified all firms of interest, the data was retrieved for the desired period. The data can be divided into three groups: (1) firm accounting data, (2) firm stock market data and (3) stock repurchase data. An overview of all variables used to construct the proxies for the hypotheses is provided in table 4.1.1a. The year-end accounting and stock market data was retrieved from Datastream using the Datastream codes and represent variables such as revenue, total assets, share price and the number of stocks outstanding. These values were gathered for each year the firm is active during the sample period. The data for the third group was, contrary to the first two groups, obtained from OneBanker and represents data regarding stock repurchase. As the stock repurchase data was obtained from a different database, the Datastream codes were used to match it with the data from Datastream. To complement this data with industry, the database Capital IQ was used to retrieve the four-digit Standard Industrial Classification (SIC) codes. As Capital IQ does not recognize the Datastream codes, the ISIN numbers were used to retrieve the needed data and match it with the rest of the sample.

Table 4.1.1a – Hypotheses, Proxies and Datastream codes

Hypothesis	Proxy	Expected sign	Datastream code
Inefficient management	Stock return	-	UP
	ROCE	-	WC01250, WC03990
Firm size	Ln Assets	-	WC02999
Revised firm size	Ln Assets^2	-	WC02999
Undervaluation	MTB	-	UP, NOSH, WC03501, WC02649
Growth resource mismatch	Liquidity ratio	+/-	WC02001, WC02999
	Leverage ratio	+/-	WC03255,WCWC03995
	Sales growth	+/-	WC01001
	GRM dummy	+	WC01001, WC02001, WC02999, WC03255
Tangible assets	TA ratio	+	WC02501, WC02999
Free cash flow	FCF	+	WC04860, WC04601, WC02999
Industry concentration	HH Index	-	WC01001
Share repurchases	SP dummy	+/-	OneBanker

Note: This table gives on overview of the hypotheses, proxies, expected coefficient signs and the Datastream variables used to compute them. Data for all proxies was extracted from Datastream using the codes presented in the rightmost column. The exception is share repurchase which was retrieved from the database OneBanker. The computation proxies and definitions of the Datastream variables are discussed in section 3.1. Stock return is the return from the previous period. ROCE is the return on capital employed. Ln assets is the natural logarithm of total assets. Ln assets^2 is the natural logarithm of total assets squared. MTB (market to book ratio) is the market value of equity to the book value of equity. Liquidity is the ratio of cash and short term investment to total assets. Leverage ratio is total debt to book value of equity ratio. Sales growth is the change in revenue from the previous period. GRM dummy is the growth-resource mismatch dummy which takes the value 1 if there is a mismatch and 0 otherwise. TA is the ratio of tangible assets to total assets. FCF (free cash flow) is the ratio of operational cash flow stripped of capital investments to total assets. Herfindahl-Hirschman Index (HHI) measures the industry concentration (see section 3.1.8). SP dummy takes the value 1 if there has been a stock repurchase and 0 otherwise.

The Datastream database is widely acknowledged and has been used by prior research in the field of takeover likelihood modelling (e.g. Powell & Yawson, 2007; Danbolt et al., 2016). However, it is important to note that it does not provide full data coverage for the variables needed across all firms and years, ultimately leading to missing values. The reliance on multiple different databases further amplified the problem of missing values as their coverage of firms is not fully coherent. The consequence is that not all firms retrieved from Datastream could be allocated data from the complementary databases (i.e. SIC codes, share repurchase and acquisition status). The consequence of the missing values resulted in a reduction from 16 918 to 9 398 unique firms present in the sample, or 138 633 to 57 635 firm-year observations, with full data coverage. This exclusion of firms year observations, due to lack of full data coverage, affected target firms relatively more compared to non-target firms (see table 4.1.3). To re-balance the dataset back to the initial proportion of target to non-target observations at 1,5%[8], an additional 34 536 randomly selected non-target firm-year observations were excluded. Thus, the total dataset was shrunk to 23 096 firm-year observations and the number of unique firms to 7 685. See table 4.1.1b for an overview of the number of observations after each exclusion step.

The remaining firms were subsequently divided into eight industry groups based on their four-digit SIC code. This division was not based on prominent previous research as the literature lacks a standard methodology but instead was similar to the division employed by Renneboog and Trojanowski (2007). The industry division employed in this study was a bit more comprehensive and included a separate group for Mining and Construction firms, Transportation and Public utility as well as Public administration. Furthermore, observations relating to financial firms (Group 6000-6999) were excluded as the distinct financial ratios of banks and insurance firms would distort the results of the analysis (see Brar et al., 2009; Ouzounis et al., 2009). Appendix 4.1.1 provides an overview of the distribution of firms and firm-year observations across different industries.

Table 4.1.1b: Training sample construction

	Firm year observations	Number of unique firms
Original (at least 1 variable)	138 633	16 918
All variables before rebalancing	57 635	9 398
Data sample after rebalancing	23 096	7685

Note: This table represents the number of observations after each filtering step. Initially 138 633 firm year observations, from 16 918 unique firms, were identified having data for one or more Datastream code variable available. After filtering out all firm year observations with missing values and rebalancing the dataset so the target to non-target ratio was 1,5% a total of 23 096 firm year observations from 7 685 unique firms remained.

4.1.2 - Holdout sample

The holdout sample is an essential part of the thesis as it was used to evaluate the trained models' predictive capabilities in out-of-sample tests. To test the true predictive power of each model, they must be tested on a separate holdout sample. For this reason, 20% of all target firm-year observations were separated from the training sample at the start of the data collection process. This holdout sample was intentionally not preprocessed with matching and not included in the model building phase to reduce bias and potential overfitting albeit at the expense of more accurate coefficients. The holdout sample was constructed from the most recent observations in the dataset to replicate a real-life setting as closely as possible. This approach was

8 This approach of using a balanced sample representing the true ratio of target to non-target firms was suggested by Palepu (1986) as a superior approach and adopted by many researchers after.

in line with prior research (e.g. Espahbodi & Espahbodi, 2003). The holdout period stretched from 2014 to 2018.

For this period, a total of 40 305 firm-year observations by 9 526 unique firms were identified having data for at least one variable. When excluding firm-year observations without full data coverage, the number was reduced to 16 633 firm-year observations by 4 632 unique firms. To re-balance the dataset and achieve a ratio of approximately 1,5% target firm observations, 9 996 non-target observations were randomly pruned from 1 035 firms. See table 4.1.2 below for an overview of the number of observations remaining after each step. Their distribution across the different industries are presented in appendix 4.1.2.

Table 4.1.2: Holdout sample construction

	Firm year observations	Number of unique firms
Original (at least 1 variable)	40 305	9 526
All variables before rebalancing	16 633	4 632
Data sample after rebalancing	6 637	3 597

Note: This table represents the number of observations after each filtering step. Initially 40 305 firm year observations, from 9 526 unique firms, were identified having data for one or more Datastream code variable available. After filtering out all firm year observations with missing values and rebalancing the dataset so the target to non-target ratio was 1,5% a total of 6 637 firm year observations from 3 597 unique firms remained.

4.1.3 - Dependent variable

Thomson Onebanker database was used to identify the complete list of successful takeover targets for both the test and holdout sample. This thesis follows the same definition of successful acquisition used by Powell and Yawson (2007). They defined takeover acquisitions as deals where the bidder owns less than 50% of the acquisition firm's stocks pre-takeover and above 50% after the completion date. Furthermore, no distinction was made regarding friendly and hostile bids in accordance with the approach adopted by a bulk of prior research (e.g. Palepu, 1986; Ambrose & Megginson, 1992; Powell, 2001; Brar et al., 2009)

When extracting the data from Onebanker, the following search criteria was employed. Searching the "All Mergers & Acquisitions" database, the target firm needed to be (1) a US firm, (2) public, (3) active between 1st of January 1999 to 31st of December 2019, and (4) the bidder had to own at least 50,1% of the shares after the transaction. The dataset was later filtered from firms that increased their ownership but already owned over 50% of the shares.

The acquisition data was later matched with the test and holdout sample using the datastream code. Many takeover targets had incompatible Datastream codes with the samples, and a minority of those who did, had complete data coverage, resulting in a substantial drop of observations. Table 4.1.3 lists the number of transactions left after each step. The 435 remaining firm-year observations with full data coverage received a dummy variable of 1 indicating they were acquired in that specific year.

Table 4.1.3: Data collection process for the dependent variable

Search Criteria	Request	Number of observations
Target Nation	US	358427
Target Public Status (Code)	Public	65860
Date Effective/Unconditional	01/01/1999 to 12/31/2019	8459
Led to a majority stake	Yes	8081
Matched with a firm present in the test and/or hold-out sample	Yes	5031
Full data coverage	Yes	435

Note: This table represents the number of available observations after each filtering step. The criteria states the bidder had to acquire a majority stake of a public US firm in the period between 01/01/1999 to 12/31/2019. This yielded 8031 target firm observations whereof only 435 had all necessary data for the construction of the independent variables.

4.1.4 - Handling of outliers

The extensive training data included observations from over 7 685 unique firms and 23 096 firm-year observations. The large dataset is beneficial as it included all of the publicly listed US firms present in Worldscope's constituents list with full data coverage[9] spanning from 2000 to 2013. As the number of observations increases, the risk of including outlier data follows. Considering that many of the hypotheses are proxied by ratios, an extreme value can potentially distort the included proxy, and thus, substantially affect the distribution of the data and regression coefficients. This is evident when observing the descriptive statistics in appendix 4.1.4a as, for instance, the variable ROCE had a mean value of 231% while the median was 16%. This was likely caused by extreme outliers.

To resolve the issue, the data was winsorized at the 5th and 95th percentile in line with Christidis and Gregory (2010), and to some extent to Danbolt et al. (2016), who similarly to this study relied on Datastream for obtaining variable data. The benefit of winsorization relative to an elimination approach is that it does not cause any loss of data. The results indicated a substantial improvement to the distribution as the mean values became more reasonable and closer to the median values (see appendix 4.1.4b). The majority of the independent variables had skewness of below 1 indicating a distribution that is not heavily skewed.

[9] Given the data collection procedure of this thesis

4.2 Matching as a method for preprocessing the data

Matching was conceptually introduced in-depth in section 2.5 of the literature review. It was mentioned that matching is employed in the design stage of the causal research, after which outcome analysis is conducted with logistic regression in this thesis. Matching is aimed at preprocessing the data to improve the balance between targets and non-targets, and consequently, improving the inferences from the outcome analysis. In this study, four matching types are implemented mainly to compare their explanatory and predictive power and to add robustness to the analysis. Additionally, three sets of matching variables are applied for each matching type for additional robustness check. Below, the distance measures and matching methods (which combined form a 'matching type') are described in more technical terms compared to the literature review. Also, the implementation of matching variable combinations are discussed briefly.

4.2.1 Distance measures

4.2.1.1 Propensity scores

Propensity scores as a distance measure for matching (PSM) require estimation of propensity scores prior to calculating the distance between two observations. Propensity scores were first introduced in a seminal study by Rosenbaum and Rubin (1983) who defined propensity scores as the probability of treatment conditional on observed covariates,

$$e(x_i) = pr(W_i = 1 \mid \mathrm{X_i} = x_i) \tag{10}$$

where X is a vector of covariates and $XW_i = 1$ represents treatment for the observation i. Thus, propensity scores fall into a scale between 0 and 1. The purpose with propensity scores is to reduce the multidimensional covariates into one dimensional single variable (Stuart, 2010), thus summarizing the information of vector X into a single score (Guo & Fraser, 2014). The reduction in dimensions makes it easier to find matches between target and non-target observations (Guo & Fraser, 2014). Generally, the true propensity scores are not known, and thus, the estimated propensity scores become the predicted probability of treatment (Dehejia & Wahba, 2002). Propensity scores are estimated most often by using a logistic regression model,

$$\pi_i = (1 + e^{-x_i\beta})^{-1} \tag{11}$$

(Abadie & Imbens, 2016; Dehejia & Wahba, 2002), which is also used as the outcome analysis model of this study and discussed more in-depth in section 4.3.2.

Once the propensity scores are estimated, the observations are arranged by the score from the lowest to the highest (Dehejia & Wahba, 2002). As propensity score is one-dimensional, the distance between the observations can simply be calculated by:

$$D_{ij} = \mid e_i - e_j \mid \tag{12}$$

, where e is the propensity score of observation i,j (Stuart, 2010). The distance measures are then used to execute the matching with the chosen matching method - these are discussed after the two other distance measures, Mahalanobis distance and coarsened exact matching.

4.2.1.2 Mahalanobis distance

Unlike propensity scores, Mahalanobis distance (MD) measures the distance between two observations in the multidimensional space (Rubin, 1980). In other words, MD does not require reducing the dimensions of the covariates into one as propensity score does, and thus, the distance can directly be calculated from the covariate values. To employ MD measure, the observations are put in random order and the distance between two observations is measured with the following formula:

$$D(X_i, X_j) = \sqrt{(X_i - X_j)' S^{-1} (X_i - X_j)} \tag{13}$$

, where X is the values of matching variables and $S - 1$ denotes the sample covariance matrix of X (Rubin, 1980).

Then, the matching is conducted with the chosen matching method - in this thesis, with the nearest neighbor. Nearest neighbor is discussed later in section 4.2.2.1.

4.2.1.3 Coarsened exact matching

Coarsened exact matching (CEM) has a foundationally different approach for matching compared to PSM and MD. According to Iacus et al.'s (2011) classification, PSM and MD belong to a matching class called "equal percent bias reducing" (EPBR) while CEM is part of a more recent development of "monotonic imbalance bounding" (MIB). EPBR matching methods choose fixed sample size ex-ante (more specifically, the number of control variables matched) but can not guarantee any level of imbalance reduction. For example, by matching with 1:1 nearest neighbor with PSM as a distance measure, the researcher would know that the final sample is two times the size of treated units (50% treated and 50% untreated units). Contrarily, with MIB matching, the user specifies the level of imbalance ex-ante but can not decide the resulting sample size from the matching procedure (King et al., 2011; Iacus et al., 2011). For instance, by matching with CEM, the researcher could ex-ante determine retail firms with 100-500 employees as a match but would not be able to define the size of the resulting sample after the matching. As with most statistical methods, the bias-variance tradeoff[10] is confronted also in matching and it is affected by a tradeoff between model imbalance and sample size (King et al., 2011). By fixing the sample size, EPBR is designed to solve the variance side of the tradeoff while MIB methods focus on the bias by reducing model imbalance (Iacus et al., 2011). For matching purposes, Rubin (2006) and Iacus et al. (2011) perceive low bias as a more important quality compared to low variance since sample sizes are often large in observational studies, and thus, the sampling variances are small, and the sensitivity of covariates to biases is the main source of uncertainty.

CEM functions via three steps: (1) each covariate is temporarily coarsened to the desired degree and re-coded so that each group has the same numerical value (e.g. grouping ages to young, middle-aged and old). (2) All of the observations are sorted into strata, where each stratum consists of observations with the same coarsened covariate values. (3) Finally, the observations are pruned in all strata that do not include both treated and control units (Iacus et al., 2009; Iacus et al., 2011). Thus in coherence with MIB, the level of imbalance is defined ex-ante by the chosen degree of coarsening.

In this thesis, automated coarsening was implemented, which specifies the cutpoints for the covariates based on Sturges' rule (Iacus et al., 2009). This approach, instead of manual coarsening, was chosen to automate the process and decrease researcher bias in defining the coarsened groups. By conducting the coarsening manually, the cutpoint selection would have been at least partially arbitrary, and thus, required multiple coarsening variations to decrease the bias. Sturge's rule is a widely implemented formula in the literature for optimizing the number of coarsened groups of which more in-depth information can be found in Scott (2009).

After the matching is conducted, the retained observations are assigned weights before continuing to the outcome analysis in order to account for the varying distributions of the control units relative to the treated units in the strata. The weighting scheme assigns a higher weight for the control observations, which are in the same strata with many treated observations.

10 The bias-variance tradeoff can be conceived as a sliding scale adjusting how intensively the statistical model adheres the training data. On one side of the scale, the model considers the training data in a very detailed level (high variance and overfitting), while on the other side of the scale, the model simplifies the training data and might fit the data poorly (high bias - underfitting) (Briscoe & Feldman, 2011).

$$w_i = \begin{cases} 1, & i \in T^s \\ \dfrac{m_C}{m_T}\dfrac{m_T^s}{m_C^s}, & i \in C^s \end{cases}. \tag{14}$$

, where T_s denotes the treated units in the stratum s, C_s the control units in the stratum s, m_T the matched treated units, m_C the matched control units, m_T^s matched treated units in the stratum and m_C^s matched control units in the stratum.

4.2.2 Matching methods

Unlike CEM, PSM and MD only measure the distances between observations, and thus, need to be combined with a specific matching method to execute the matching. The matching methods implemented in this study are nearest neighbor with caliper and full matching. There are other methods available as discussed earlier in the section 2.5.2. Due to the strata approach of CEM, it inherently is both a distance measure and a matching method.

4.2.2.1 Nearest neighbor with caliper

Generally, the nearest neighbor method matches the closest observations by using either the PSM or MD as the distance measure. More specifically, the chosen 1:1 nearest neighbor method with caliper matches one control observation with each treated observation and requires the distance to be within a pre-specified range (the caliper) (Stuart, 2010). Thus, the resulting training sample consists of 50% treated and 50% control units. All the control units not matched with treated units were pruned, and if for some treated units, there were no control units within the caliper, they were pruned as well.

Caliper has mainly been implemented to avoid poor matches, and therefore to increase the quality of the covariate distribution between treated and control groups. The downside and tradeoff is that the caliper might have led to many treated observations not being matched, and thus decreasing the sample size and complicating the interpretation of the outcome analysis (Stuart, 2010; Rosenbaum & Rubin, 1985a). Caliper sets the boundaries in terms of standard deviations of the selected distance measure, and within those boundaries, the 1:1 matching is executed with the two nearest observations measured by the same distance measure. For PSM, a caliper of 0.25 standard deviations, which was originally suggested by Rosenbaum and Rubin (1985b) and has been widely used in the previous literature, was adopted in this study. For Mahalanobis distance, there is not standard caliper, and therefore, 0.25 standard deviations was applied as well. Below the 1:1 matching with caliper is defined mathematically:

Propensity scores:

$$\chi = min \mid Z_i - Z_j \mid, \text{if} \quad \mid Z_i - Z_j \mid \leq C \tag{15}$$

, where Z is the propensity score and C is the caliper.

Mahalonobis distance:

$$X = \min\left(\sqrt{(Y_i - Y_j)' S^{-1} (Y_i - Y_j)}\right) \ , \ if \ \ \chi = \min\left(\sqrt{(Y_i - Y_j)' S^{-1} (Y_i - Y_j)}\right) \leq C \tag{16}$$

, where Y is the values of the matching variables and C is the caliper.

4.2.2.2 Full matching

Full matching divides the observations into subclasses, where the matched subclasses contain at least one treated and control observation but may include many from either group. Full matching minimizes the average distance within the subclasses, and thus, the resulting subclassifications are optimal (Gu & Rosenbaum, 1993). Instead of pruning the observations like with nearest neighbor, full matching assigns weights between 0 and 1 for the observations in the resulting subclasses (Stuart, 2010).

Full matching only discards units that are outside of the common support, thus reducing pruning compared to the nearest neighbor with caliper approach introduced above (Ho et al., 2011). Common support refers to the area, which both the treated and controlled observations cover (Stuart, 2010). Therefore, full matching is better aligned with the previous critique from the takeover prediction literature regarding pruning observations in matching (eg. Bartley & Boardman, 1990) as was discussed earlier in section 2.5.2. Full matching is only used with PSM as the distance measure due to the requirement for a single distance measure to create the subclasses (Stuart, 2010).

4.2.3 Matching variables

The implemented matching variables were introduced in section 3.2 of the hypotheses development chapter and include takeover year, risk of bankruptcy and industry. Risk of bankruptcy is measured by Ohlson's O-score (see section 3.2.1) and industry was determined by SIC codes (see section 4.1.1). The base combination of matching variables used in this study included takeover year and risk of bankruptcy. This was due to industry concentration being employed as one of the prediction hypotheses, and thus, creating an overlap with using industry as a matching variable. Therefore, industry was included as a matching variable for two alternative variable combinations to increase robustness within the comparison of matching types. Due to the overlap, industry concentration was removed from the multivariate analysis when the matching variable combinations including industry were implemented. This approach was in line with e.g. Brar et al. (2009). The variable combinations are displayed below in table 4.2.3.

Table 4.2.3: Matching variable combinations

Variable combination	Takeover year	Risk of bankruptcy	Industry
Base	x	x	
Alternative 1	x	x	x
Alternative 2	x		x

Notes: This table presents the variation of matching variables used in the study. The different combinations of matching variables is necessary due to overlap with independent variables but also serves as a robustness check. The base combination of matching variables includes takeover year and risk of bankruptcy. Alternative 1 includes takeover year, risk of bankruptcy and industry. Alternative 2 includes takeover year and industry. Takeover year is the year of acquisition. Risk of bankruptcy is accounted for by Ohlson’s O-score. Industry is accounted for by SIC codes.

4.2.4 Implementing matching

To pre-process the dataset with the matching procedures presented above, MatchIt package for programming language R was used. MatchIt is a comprehensive package with the most sophisticated range of matching procedures available including all of the distance measures and matching methods discussed above. After executing the matching with MatchIt, it allows the freedom of continuing the analysis with any quantitative model and any other software package that the researcher would have used otherwise (Ho et al., 2011).

In total, four matching types have been implemented in this paper; these include the combinations of the selected distance measures and matching methods. Model without matching has been used as a benchmark. The matching types with the corresponding key selections on the MatchIt software package is presented below in table 4.2.4. The outcome analysis with logit regression has been employed after the matching similarly as without matching. The only exception is that weight was added to the regression for CEM and full matching with PSM.

Table 4.2.4: Matching types

Matching type	Distance measure	Matching method	MatchIt
	No matching	No matching	-
P-NN	PSM	NN with caliper	Distance = "logit", method = "nearest", ratio = 1, caliper = 0.25
M-NN	MD	NN with caliper	Distance = "mahalanobis", method = "nearest", ratio = 1, caliper = 0.25
M-FM	PSM	Full matching	Distance = "logit", method = "full", discard = "both"[11]
CEM	CEM	CEM	method = "CEM"

Notes: This table presents an overview of the different matching types (and lack of) which have been implemented in this thesis. A matching type is a combination of distance measure and matching method. The MatchIt column represent the key selections made to produce a regression with said matching type. P-NN is the abbreviation for the distance measure propensity score matching (PSM) combined distance measure nearest neighbor with caliper. M-NN is the abbreviation for the distance measure Mahalanobis Distance (MD) combined with the distance measure nearest neighbor with caliper. M-FN is the abbreviation for the distance measure propensity score matching (PSM) and matching method full matching. CEM is the abbreviation for the distance measure Coarse exact matching (CEM) which is bundled with its own matching method.

4.3 Hypothesis validation

This section explains the methodology employed in validating the hypotheses and evaluating the explanatory power between the models. The methodology employed for hypothesis validation through univariate and multivariate analysis is explained in sections 4.3.1 and 4.3.2. In section 4.3.3 the decision criteria for hypothesis validation is defined, section 4.3.4 deals with multicollinearity and 4.3.5 presents a robustness test for the revised firm size hypothesis due to the expected curvilinear relationship. Finally, the measure of explanatory power, pseudo R^2 is explained in section 4.3.6.

4.3.1 Univariate analysis

Univariate statistical tests were conducted to investigate the validity of the relationship between a single independent variable and the dependent variable. The tests work by investigating an independent variable's ability to differentiate between two states/groups, in this case target or non-target. Although there are a number of different univariate tests available, most studies in prior takeover likelihood literature rely solely on the T-test (see e.g. Ambrose & Megginson, 1992; Powell, 1997; Brar et al., 2009; Danbolt et al., 2016). Therefore, this thesis employed a Welch T-test given its superior robustness towards variations in variance between the two groups compared to other t-test alternatives (Ruxton, 2006). A critical assumption of the chosen t-test is

[11] Discard="both" refers to the area of common support discussed in section 4.2.2.2.

that the training sample data is normally distributed (Delacre et al., 2017). Kwak and Kim (2017) state that if the sample size is sufficiently large, the central limit theorem argues that the means of the two groups will converge towards the true distribution means. Given the size of the employed sample, the normality assumption was considered fulfilled.

4.3.2 Multivariate analysis

As mentioned in section 2.4.1 of literature review, the logit model was implemented in this study due to its theoretical superiority among the parametric models. The theoretical superiority was related to the relaxed assumptions of multivariate normality (Barnes, 1999) and linear relationships between dependent and independent variables. The only constraint for logit regression, according to Barnes (2000), is that the assumption regarding truly independent explanatory variables needs to be fulfilled. This assumption of independence was tested by computing and examining variance inflation factor (VIF) scores and a correlation matrix (Moutinho & Hutcheson, 2011) for multicollinearity. The assumption was fulfilled and further discussed in the following section (4.3.4). Since the focus of this paper was not on improving the methodology related to choice of outcome model, no competing models were implemented.

As explained by Palepu (1986), the probability of a firm being acquired within a certain period depends on the number, and type, of bids it receives in the given period. These bids are in turn assumed to be dependent on firm characteristics and takeover motives of the acquirer. As all of these variables cannot be quantitatively measured, or otherwise estimated, they are assumed to be stochastic.

Therefore, Palepu (1986) argued that if the number of acquirers and their acquisition motives were to be considered stochastic, a firm's takeover likelihood could be seen as a logit function of its operating environment and firm characteristics. Accordingly, the logit model classifies a firm as either target or non-target based on its conditional takeover likelihood (Espahbodi & Espahbodi, 2003). The likelihood of a firm being acquired at time t is therefore modelled to be conditional on its observed characteristics in the period(s) prior to t. The model is based on the logistic regression which assumes a sigmoid shaped relationship (S-shaped) between a binary dependent variable (in this case target or non-target) and a combination of independent variables (hypotheses) modelled by X_i (Stock & Watson, 2015).

$$\Pr(Y = 1 \mid X_1, X_2, \dots, X_n) = F(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n) \tag{17}$$

In the equation above, F is the cumulative standard distribution function $1/(1 + e^{z_i})$for the random variable z_i, β_i is the estimated coefficients and X_i are the independent variables. The coefficients (β) are estimated using maximum likelihood meaning that the coefficients, which generate the highest log-likelihood for the model, are chosen (Stock & Watson, 2015). Further, this means that the higher the log-likelihood the better the sigmoid shaped line fits the data. The independent variables include all hypotheses with the exception of the revised firm size hypothesis as it was deemed insignificant. Instead, the traditional firm size hypothesis was significant, and therefore, included. The logit model was additionally used to test the significance of the hypothesized relationships of the explanatory variables. This was primarily done by relying on the standard errors and p-values.

As discussed in section 4.1, the training sample consisted of a panel dataset of all public US firms available between 2000-2013[12]. The panel data approach uses firm years instead of firms. This means that specific firms, which are not acquired or bankrupted immediately, are observed repeatedly across several years possibly leading to clustering and correlation in the measured residuals. This would violate the assumption of logit regression, which assumes that the standard errors of firms present in the sample are uncorrelated. If this problem is not investigated, the inferences might be incorrect about the determinants of takeover likelihood, thus leading to erroneous results. Furthermore, the studies by Mitchell and Mulhering (1996) and Mulherin and Bone (2000) indicate that takeovers can cluster over time and across industries. Therefore, standard errors were adjusted for clustering in regard to time, industry and firm as a robustness check. These three adjustments are included in the multivariate results (table 5.1b) as models 1F-1H. This robustness test was also suggested by Powell and Yawson (2007).

4.3.3 Validation of hypotheses

Both univariate and multivariate analyses were used in assessing the validity of the hypotheses. Due to the theoretical superiority of multivariate analysis, it was assigned the majority of the weight in hypothesis validation. In total, nine models were assessed of which eight were multivariate models (four with various matching types, three with robust clustered standard errors and one without either). Multiple models were used in the hypothesis validation process for added robustness.

The decision criteria was simple: the majority of the models had to support the hypothesis to get validated. This indicated that the hypothesized relationship for the variable had to be correct (sign of coefficient) and statistically significant at 5% level (p-value).

[12] All publicly listed US firms filing with the Security Exchange Commission (Thomson Reuters, 2015) and which have full data coverage given the employed data extraction methodology are included in the training sample (See section 4.1.1).

4.3.4 Multicollinearity

As can be interpreted in the hypotheses development section, a number of the included hypotheses stem from similar and/or interconnected theories. Some of the included hypotheses (and variables) are, therefore, potentially subject to being correlated to one another. Drawbacks of multicollinearity include inflated standard errors and wide confidence intervals (Brooks, 2019). In the event of unacceptable levels of multicollinearity, the estimated coefficients become imprecise, sensitive to minor changes in the model and highly dependent on the included independent variables. High degrees of multicollinearity can even reverse the signs of coefficients (Hair et al., 2019) and provide unreliable p-values used to validate hypotheses (Brooks, 2019). Thus, multicollinearity is an important condition to examine. To investigate if the level of multicollinearity was within an acceptable threshold, a correlation matrix, VIF scores and tolerance scores were computed.

The tolerance score measures how much of the variation of a particular variable cannot be explained by all other independent variables. Tolerance ranges between 0 and 1. A high tolerance score indicates that the remaining independent variables are bad at explaining its variance and suggest the presence of low multicollinearity (Hair et al.,2019). The VIF score is calculated as the inverse of the tolerance score and represents the factor by which the variance is inflated due to multicollinearity, thus giving it the name Variance Inflation Factor. This means that the square root of the VIF score measures the factor by which standard errors increase for a particular independent variable due to multicollinearity. The increase in standard errors expands the confidence intervals around the estimated coefficients, subsequently making it harder to prove that the coefficients significantly differ from zero. Hair et al. (2019) further argues that if there are VIF scores above 3 then there could be multicollinearity issues with the dataset.

The VIF and Tolerance scores are presented in table 4.3.4 while the correlation matrix is available in appendix 4.3.4.

Table 4.3.4 - Multicollinearity

Hypothesis	Variable	Tolerance	VIF	Tolerance	VIF
		Without revised firm size		*With revised firm size*	
Inefficient management	Stock return	0,949	1,054	0,945	1,058
	ROCE	0,593	1,686	0,588	1,702
Firm size	Firmsize	0,516	1,937	0,010	102,369
Revised firm size	Revised firm size	-	-	0,010	100,014
Firm undervaluation	MTB	0,744	1,344	0,755	1,325
Growth-resource mismatch	Liquidity	0,718	1,393	0,694	1,441
	Leverage	0,718	1,392	0,735	1,36
	Sales Growth	0,951	1,052	0,947	1,056
	GRD	0,842	1,188	0,840	1,191
Tangible assets	Tangible assets	0,838	1,194	0,845	1,184
Free Cash Flow	FCF	0,565	1,771	0,462	2,163
Industry concentration	Ind concentration	0,785	1,274	0,675	1,481
Share repurchase	Share repurchase	0,985	1,016	0,986	1,015

Notes: This table shows variance inflation factor (VIF) scores for all independent variables included in this study both with and without the polynomial revised firm size variable. The results show that for the VIF scores estimated without the polynomial revised firm size variable all scores are below the threshold of 3 suggested by Hair et al. (2019), where a lower VIF score is better. The exception is firm size and revised firm size when both are included in the same regression. The independent variables are presented and discussed in section 3.1. Stock return is the one year return based on stock price. ROCE is the return on capital employed computed as EBITDA divided by total capital employed. Firm size is the natural logarithm of total assets. Revised firm size the natural logarithm of total assets squared. MTB is the market value of equity to book value of equity. Liquidity is the ratio of cash and short term investments to total assets. Leverage is the ratio of debt to equity. Sales growth is the one year growth in sales. GRD is the growth resource mismatch dummy which takes the value 1 if there is a mismatch and 0 otherwise. Tangible assets is the ratio of property, plant and equipment to total assets. Industry concentration is the Herfindahl–Hirschman Index that measures the firm's industry concentration on a yearly basis. Share repurchase is a dummy which takes the value 1 if a firm has conducted a share repurchase in the previous year and 0 otherwise.

When assessing the VIF scores (excluding revised firm size proxy), all variables were below the threshold, indicating that the sample's multicollinearity was modest at most. The correlation matrix validated this as all bivariate coefficients were below the threshold of 0,7 suggested by Dormann et al. (2013) (appendix 4.3.4).

The results were different when assessing the VIF and tolerance scores by including the polynomial revised firm size proxy. The presence of a high level of multicollinearity was likely to cause issues in estimating and validating the coefficients in multiple regression, wherefore, an additional robustness test for curvilinear relationships needed to be conducted. Hair et el. (2019) suggested that piecewise regression tests of significance should be conducted for polynomial terms. The test is discussed more in-depth in the following section 4.3.5.

4.3.5 Robustness test for the revised firm size hypothesis

As discussed in the hypothesis development section 3.1.3, the revised firm size hypothesis was expected to have a concave relationship with takeover likelihood. This was investigated by adding a squared term to the logistic regression model and testing for significance. The use of the polynomial term caused multicollinearity issues to the model as indicated in the previous section, thus possibly impacting the estimated coefficients of all variables incorrectly. Therefore an additional robustness test is required.

The employed robustness check involved conducting a segmented (also known as piecewise) regression. The segmented regression assumes breakpoints in the relationship between the independent and dependent variable (Gujarati & Porter, 2009). As the revised firm size hypothesis assumed a curvilinear relationship with acquisition likelihood it was expected that the coefficient would change sign from positive to negative as the log value of total assets increases. To measure if the curvilinear relationship holds, the observations were divided into five equally large segments based on firm size - measured by the natural logarithm of total assets. A multivariate logit regression (see section 4.3.2) was then run for each segment with the expectation to observe a concave relationship in the coefficient as. The equation for the model is as follows:

$$Logit(Pr_i) = \begin{bmatrix} \gamma_0 + \gamma X_{1,i} \sum \gamma_c X_{c,i} + \varepsilon, & X_{1,i} \leq p20 \\ \delta_0 + \delta X_{1,i} \sum \delta_c X_{c,i} + \varepsilon, & p20 < X_{1,i} \leq p40 \\ \tau_0 + \tau X_{1,i} \sum \tau_c X_{c,i} + \varepsilon, & p40 < X_{1,i} \leq 60 \\ \upsilon_0 + \upsilon X_{1,i} \sum \upsilon_c X_{c,i} + \varepsilon, & p60 < X_{1,i} \leq p80 \\ \theta_0 + \theta X_{1,i} \sum \theta_c X_{c,i} + \varepsilon, & X_{1,i} > p80 \end{bmatrix} \tag{18}$$

For firms in the bottom 20th percentile, γ_o represents the constant term, γ the slope of coefficient, $X_{1,i}$ the value of the independent variable (ln total assets), $\sum Y_c X_{c,i}$ is a set of control variables and ε the error term. Pr_i represents the probability of acquisition.

The hypothesis predicts that the coefficient γ should be positive for segment "$X_{1,i} \leq p20$ " and coefficient θ negative for " $X_{1,i} > p80$ ". Depending on the distribution and degree of curvature coefficient δ should also be positive, although less so than γ, and ν negative, although less than θ. This means that if the revised firm size hypothesis is to hold a concave relationship should be expected between takeover likelihood and the natural logarithm of total assets.

4.3.6 Explanatory power

The most common way to evaluate and compare regression models is through assessing their overall fit measured by R^2. In other words, this measure describes how well the independent variables explain the variation in the dependent variable. There is not a single true R^2 measure for logistic regressions although several "R^2"-like measures have been developed (e.g. McFadden's R^2, Negelkerge's R^2 and Cox and Snell's R^2) (Brooks, 2019; Hair et al., 2019). These pseudo R^2, as they are called, are interpreted in a similar, but not identical, way to the famous coefficient of determination in linear regression (regular R^2) (Hoetker, 2007). Most of these pseudo R^2 generate values between 0 and 1, where the latter indicates a perfect fit (Hair et al., 2019). This means that the pseudo R^2 lacks the simple interpretability of the more traditional R^2. It is important to note that different pseudo R^2 measures vary extensively in terms of magnitude and there is no prefered version. Long and Freese (2006) therefore argue that the pseudo R^2 can only be compared to other pseudo R^2s of the same type, which are estimated from the same dataset and use the same dependent variable.

This thesis employed the McFadden pseudo R^2 given its adoption in previous literature (e.g. Palepu, 1986). It is computed as follows:

$$R^2 = 1 - \frac{LLF}{LLF_0} \tag{19}$$

, where LLF is the log-likelihood of the fitted[13] model and LLF_0 is the log-likelihood of a null model, which consists only of the intercept (i.e. the coefficients are set to zero).

The ratio between the log likelihoods quantifies the level of improvement of the fitted model over the null model. A small ratio indicates that the fitted model is far superior compared to the null model which ultimately results in a higher pseudo R^2 score (Stock & Watson, 2015). Furthermore, the explanatory power for all pseudo R^2 values generally tends to be significantly lower compared to the more traditional R^2. Hair et al. (2019) states that this is due to the dependent variable being binary while the prediction is made based on probability values.

4.4 Predictive analysis

The previous sections of methodology, 4.2 and 4.3, focused mainly on the explanatory analysis with discussions around pre-processing the data with matching and conducting the outcome analysis with logit regression. This section is concentrated on the second part of the analysis, the out-of-sample predictive capability.

[13] The fitted model should represent the maximized value of the log-likelihood function.

Out-of-sample predictive analysis includes employing the takeover likelihood model for the holdout sample to derive the takeover likelihoods for the observations, classifying the observations into targets and non-targets based on cut-off probability, and finally calculating the predictive performance. The next section, 4.4.1, introduces the chosen method to calculate the cut-off probabilities and 4.4.2 presents the performance measures for the predictive power.

4.4.1 Cut-off probability

Defining the optimal cut-off probability for classifying firms as targets and non-targets depends on the decision context (Palepu, 1986), which consequently specifies the classification rule (Powell, 2001). Calculation of cut-off probability is essentially a tradeoff between committing a type 1 (a target incorrectly classified as a non-target) or type 2 error (a non-target incorrectly classified as a target) (Powell, 2001). The classification rule defines the policy on how to balance the two errors. The implemented classification rules have been two-folded as discussed in earlier in section 2.4.3. Palepu (1986) and Espahbodi and Espahbodi (2003) minimized absolute number of misclassifications (type 1 and 2 errors perceived as equal and constant), while Powell (2001) maximized the proportion of target firms among the predicted targets (type 1 and 2 error neither equal nor constant).

In this paper, the decision context is not limited to a single specific group. As introduced in section 2.2, takeover prediction is of relevance to at least management teams, investors, policy makers and researchers using takeover likelihoods as an independent variable. Therefore, this study takes a neutral stand on the tradeoff between type 1 and type 2 errors and implements the classification rule minimizing the total error. The cut-off probability, given the classification rule to minimize the total misclassifications, is derived as the intersection between the probability density function of targets and the probability density function of non-targets (Palepu, 1986). The cut-off probability is calculated from the training sample and differs for each model.

4.4.2 Measuring out-of-sample predictive power

The predictive power of the models is measured with performance metrics based on the confusion matrix. Confusion matrix is simply a two-dimensional matrix with one dimension representing the true class of takeover state (target or non-target) and the other dimension displaying the predicted state (Sammut & Webb, 2011). It consists of four cells representing the correctness of the predictions: true positives (TP), false positives (FP), true negatives (TN) and false negatives (FN). The performance metrics based on confusion matrix, which are applied in this thesis include accuracy, precision and recall. These are some of the most widely used metrics for predictive power of classification model (Powers, 2011).

Accuracy is a measure of how many of the predicted observations are classified correctly, and thus, the equation of accuracy is TP+TF/TP+TF+FP+FN or alternatively correct classification/all classifications. Recall is the proportion of positives predicted correctly - the percentage of targets predicted correctly as targets. It's calculated as TP/TP+FN. Precision, on the other hand, measures the proportion of correct predictions from observations predicted positive and is measured as TP/TP+FP. With takeover predictions, precision is the share of targets from all observations predicted as targets.

Precision is, perhaps, the most informative indicator of the model's predictive performance with takeover predictions since accuracy and recall can simply be increased by adjusting cut-off probabilities. By increasing the cut-off probability, more and more observations would be classified as non-targets, thus improving accuracy closer to the ratio between non-targets to all observations (98,78% in this thesis). The high ratio between non-targets to targets is due to the rare event problem of takeovers. Contrarily, by decreasing the cut-off probability more and more observations would be classified as targets, thus increasing recall closer to 100%. The reasoning above might explain why recent literature on takeover predictions has emphasized precision as the main performance measure of predictive power (eg. Danbolt et al., 2016; Tunyi, 2019).

5. Results

This chapter presents the results from the univariate t-test and multivariate logit regressions. The regression results were used to validate the takeover hypotheses (5.1) developed in chapter 3. Several multiple regression models were constructed for added robustness in validating the hypotheses. These included models with and without matching and adjusting for clustered standard errors. Validating a hypothesis means that it possesses discriminatory capability in differentiating target firms from non-targets. If the coefficient of the variable was significant and in line with the theorized relationship with takeover likelihood, it was considered validated. The decision rule for hypothesis validation was simply that the majority of the implemented models had to support the hypothesis (see 4.3.3 for more details). Finally, the different matching types were assessed in terms of the explanatory power (5.2). The regressions were conducted using the training sample containing 354 target observations and 23 096 non-target observations between 2000-2013.

5.1 Hypotheses evaluation

The validity of the hypotheses was tested with univariate and multivariate tests using the winsorized training sample discussed in section 4.1.4. The univariate analysis consisted of a Welch two-sample t-test measuring difference in means between target and non-target firms across all variables. The multivariate analysis consisted of the logit regression model, which uses maximum likelihood to estimate coefficient parameters associated with each variable. To validate the statistical significance of the coefficients, p-values were computed based on the standard errors. Several different multivariate tests were conducted based on different matching types and additional robustness checks were conducted by adjusting for clustered standard errors based on year and industry. The descriptive statistics, including the results from the univariate statistical test, are included in table 5.1a.

Table 5.1a: Univariate analysis

Hypothesis	Proxy	Mean non-targets	Mean targets	Mean difference
Inefficient management	Stock return (-)	0,032	0,096	0,064***
	ROCE (-)	-0,033	-0,164	-0,130***
Firm size	Ln Assets (-)	11,259	10,937	-0,322***
Revised firm size	Ln Assets^2 (-)	138,629	129,626	-9,004***
Firm undervaluation	MTB (-)	1,726	1,054	-0,672***
Growth-resource mismatch	Liquidity ratio (+/-)	0,238	0,243	0,005
	Leverage ratio (+/-)	0,406	0,398	-0,008
	Sales growth (+/-)	0,179	0,082	-0,096***
	GRM dummy (+/-)	0,214	0,239	0,024
Tangible assets	TA ratio (+)	0,258	0,236	-0,022**
Free Cash Flow	FCF (+)	-0,267	-0,303	-0,036
Industry concentration	HH Index (-)	0,000	9,12E-07	-5,03E-07***
Share repurchase	SP dummy (-)	0,049	0,021	-0,027***

Notes: The table represents the results of Welch two sample t-test. Mean non-targets and targets represent the mean values for the hypothesis proxies (the independent variables to be used in logit regression). Mean difference is simply the difference between these two values. Stock return is the return from the previous period. ROCE is the return on capital employed. Ln assets is the natural logarithm of total assets. Ln assets^2 is the natural logarithm of total assets squared. MTB (market to book ratio) is the market value of equity to the book value of equity. Liquidity is the ratio of cash and short term investment to total assets. Leverage ratio is total debt to book value of equity ratio. Sales growth is the change in revenue from the previous period. GRM dummy is the growth-resource mismatch dummy which takes the value 1 if there is a mismatch and 0 otherwise. TA is the ratio of tangible assets to total assets. FCF (free cash flow) is the ratio of operational cash flow stripped of capital investments to total assets. Herfindahl-Hirschman Index (HHI) measures the industry concentration (see section 3.1.8). SP dummy takes the value 1 if there has been a stock repurchase and 0 otherwise. The brackets next to the names represent the hypothesized relationship with takeover likelihood. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The univariate results suggest that nine out of 13 independent variables significantly differ (in 5% level) in mean between target and non-target firms. The only invalidated hypotheses were growth-resource mismatch and free cash flow.

The test results from logit models are gathered below in table 5.1b. Each model regresses all independent variables against the dependent variable (target/no-target) but varies in matching type or clustering of standard errors. Model 1A is the base model without matching or robust clustered standard errors. Model 1B, 1C, 1D, 1E implement the different matching types: Model 1B uses nearest neighbor with propensity scores (P-NN), model 1C uses full matching with propensity scores (P-FM), model 1D uses coarsened exact matching (CEM) and model 1E uses nearest neighbor with Mahalanobis distance (M-NN). Models 1F, 1G and 1H adjust for clustered standard errors for correlation across industry, year and firm respectively and do not use matching.

Table 5.1b: Multivariate regression results

Hypothesis	Proxy	1A	Matching 1B: P-NN	Matching 1C: P-FM	Matching 1D: CEM	Matching 1E: M-NN	RCSE 1F: Industry	RCSE 1G: Year	RCSE 1H: Firm
Inefficient management	Stock return (-)	-0,207**	-0,243**	-0,271***	-0,148*	-0,066	-0,207***	-0,207**	-0,207*
	ROCE (-)	-0,123*	-0,045	-0,365***	-0,044	-0,021	-0,124**	-0,124**	-0,124**
Firm size	Ln Assets (-)	-0,003**	-0,002	-0,003**	-0,001	-0,002	-0,002***	-0,003**	-0,003**
Firm undervaluation	MTB (-)	-0,082***	-0,037	-0,119***	-0,071***	-0,081**	-0,082***	-0,082***	-0,082***
Growth-resource mismatch	Liquidity ratio (+/-)	-0,437	-0,629	-1,119**	-0,227	-0,485	-0,437	-0,437	-0,437
	Leverage ratio (+/-)	0,172***	0,238***	0,372***	0,091*	0,079	0,172***	0,172***	0,172***
	Sales growth (+/-)	-0,385**	-0,272	-1,012***	-0,395**	-0,527**	-0,385**	-0,385**	-0,385**
	GRM dummy (+/-)	-0,019	0,008	-0,356**	-0,027	-0,091	-0,019	-0,018	-0,018
Tangible assets	TA ratio (+)	-0,3358	-0,06756	-0,705**	-0,452*	-0,427	-0,336	-0,336	-0,336
Free Cash Flow	FCF (+)	0,576**	0,183	-0,535**	0,5263**	0,446	0,576***	0,576**	0,576**
Industry concentration	HH Index (-)	-11800	-14490	-13590*	-11760	-10440	-11802	-11802	-11802
Share repurchase	SP dummy (-)	-0,966*	-0,711	-0,907**	-0,914**	-0,940**	-0,968***	-0,968***	-0,968***
Intercept		-3,366***	0,493*	-3,800***	-3,500***	0,725***	-3,366***	-3,366***	-3,366***
Pseudo R^2		0,023	0,034	0,103	0,004	0,033			

Notes: The table represents the results of the logit model where the independent variables are the prediction hypotheses and the dependent variable is the takeover status (target/non-target). Model 1A is the base model without matching or clustered standard errors. Model 1B, 1C, 1D, 1E implement the different matching types: Model 1B uses nearest neighbor with propensity scores (P-NN), model 1C uses full matching with propensity scores (P-FM), model 1D uses coarsened exact matching (CEM) and model 1E uses nearest neighbor with Mahalanobis distance (M-NN). Models 1F, 1G and 1H compute robust clustered standard errors (RCSE) for correlation across industry, year and firm respectively and do not use matching. Stock return is the return from the previous period. ROCE is the return on capital employed. Ln assets is the natural logarithm of total assets. MTB (market to book ratio) is the market value of equity to the book value of equity. Liquidity is the ratio of cash and short term investment to total assets. Leverage ratio is total debt to book value of equity ratio. Sales growth is the change in revenue from the previous period. GRM dummy is the growth-resource mismatch dummy which takes the value 1 if there is a mismatch and 0 otherwise. TA is the ratio of tangible assets to total assets. FCF (free cash flow) is the ratio of operational cash flow stripped of capital investments to total assets. Herfindahl-Hirschman Index (HHI) measures the industry concentration (see section 3.1.8). SP dummy takes the value 1 if there has been a stock repurchase and 0 otherwise. The brackets next to the names represent the hypothesized relationship with takeover likelihood. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively

5.1.1 Inefficient management

The inefficient management hypothesis was developed in section 3.1.1 and predicts that underperforming firms are more likely to become takeover targets. It builds on the theories of market for corporate control and agency cost. The theories stipulate that underperforming management will be replaced by a more efficient management team that can create superior value for the shareholders. The variables included to proxy this hypothesis are return on capital employed (ROCE), intended to measure historic firm performance, and stock return, intended to measure the market's future expectations of management performance.

In line with the hypothesis formulation, the results from the univariate analysis (table 5.1a) confirm that there is a significant difference in means across target and non-target firms when it comes to ROCE and stock return. This suggests the two proxies possess a discriminatory ability.

The univariate analysis results are further supported by the multivariate analyses (table 5.1b) conducted in models 1A-H. All models unanimously distinguish a negative relationship between both measures of management efficiency and takeover likelihood. For stock returns, this is emphasized by six models, A, B, C, F and G, all having statistically significant results in a 5% level for the negative relationship. When assessing the relationship between historic managerial performance measured by ROCE, models C, F, G and H provide significant results. These results suggest that target firms' managerial capabilities are inferior suggested by both historical performance (ROCE) and expected future performance (stock return). Furthermore, the fact that target firms experience lower sales growth further strengthens the argument of management inefficiency. The evidence of the statistical tests suggests that the hypothesis should be validated. This conclusion is supported by studies such as Palepu (1986), Barnes (2000), and Brar et al. (2009), all of whom find support for this hypothesis.

5.1.2 Firm Size

The firm size is one of the most consistently used hypotheses in the takeover literature. It suggests that takeover likelihood is inversely related to firm size (Palepu, 1986) as the transaction costs associated with an acquisition increase with firm size. Additionally, the number of potential bidders who can afford to acquire a specific firm decreases as firm size increases. The theory behind this hypothesis is discussed more in-depth in section 3.1.2.

The inverse relationship between firm size and takeover likelihood is empirically supported on the univariate test. As shown in table 5.1a, the average non-target firm has a lognormal total asset size of 11,259 (equivalent to $77,5M) while the average target has a firm size of 10,937 (equivalent to $56,2M) as evident. The difference in size is significant at the 1% level.

This is further supported by the results of the multivariate analyses (table 5.1b) where all models show a negative coefficient. The majority of the multivariate models found the negative relationship significant in the 5% level including model A and C as well as the three models with robust clustered standard errors (F, G and H). Taking both multivariate and univariate results into consideration, the firm size hypothesis is validated. These findings are in line with a multitude of previous studies including Hasbrouck (1985), Powell (1997), Powell (2001) and Brar et al. (2009).

5.1.3 Revised firm size

The revised firm size hypothesis incorporates additional theories compared to the original firm size hypothesis proposed by Palepu (1986). When accounting for these new theories, the previously assumed negative relationship between firm size and takeover likelihood morphs into a curvilinear one. This entails that firm's takeover likelihood is expected to increase with the size until passing a specific threshold, after which the likelihood is hypothesized to start declining. This is due to a lower number of firms, which can afford to acquire the firm. The full discussion is available in section 3.1.3.

To investigate the validity of the revised firm size hypothesis, a robustness test for the curvilinear relationship was conducted by employing a piecewise regression. As explained in section 4.3.5 of methodology, firms were split into five groups based on firm size to evaluate the curvilinearity. Table 5.1.3 presents the results of the piecewise regression. Due to a lack of significant coefficient values and a clear trend among the five groups, the robustness test does not imply a curvilinear relationship for firm size between targets and non-targets. However, it must be noted that the positive coefficient for group 1 and the negative coefficient (although insignificant) for group 5 are in accordance with the revised firm size hypothesis.

Table 5.1.3 – Piecewise regression

Piecewise regression		Partition 1 0-20 percentile	Partition 2 20-40 percentile	Partition 3 40-60 percentile	Partition 4 60-80 percentile	Partition 5 80-100 percentile
Firm size	Ln(Total assets)	0,0186**	-0,0014	0,0128	0,0038	-0,0107
	Control variables	Yes	Yes	Yes	Yes	Yes
	Intercept	Yes	Yes	Yes	Yes	Yes

Notes: This table presents results of logit regressions with no matching variables for different quintiles of firm size where the dependent variable is bivariate and represents whether a firm is a target firm or not. The independent variables are firm size proxied by the natural logarithm of total assets. The control variables are Stock return, ROCE, MTB, liquidity, leverage, sales growth, Growth-resource mismatch dummy, tangible assets ratio, FCF, industry concentration, share repurchase dummy. Stock return is the return from the previous period. ROCE is the return on capital employed. Ln assets is the natural logarithm of total assets. MTB (market to book ratio) is the market value of equity to the book value of equity. Liquidity is the ratio of cash and short term investment to total assets. Leverage ratio is total debt to book value of equity ratio. Sales growth is the change in revenue from the previous period. GRM dummy is the growth-resource mismatch dummy which takes the value 1 if there is a mismatch and 0 otherwise. TA is the ratio of tangible assets to total assets. FCF (free cash flow) is the ratio of operational cash flow stripped of capital investments to total assets. Herfindahl-Hirschman Index (HHI) measures the industry concentration (see section 3.1.8). SP dummy takes the value 1 if there has been a stock repurchase and 0 otherwise. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Although the piecewise regression rejected the revised firm size hypothesis, a multivariate model with the hypothesis was constructed as an additional check. The results are shown in appendix 5.1.3. The results supported the hypothesis by reporting a positive non-polynomial term and negative polynomial term.

As the piecewise regression was considered a more robust measure for validating the revised firm size hypothesis, it was not validated. However, the multivariate results were optimistic and the hypothesis might be of interest to future research.

5.1.4 Firm undervaluation

The firm undervaluation hypothesis stipulates that undervalued firms are more likely to become takeover targets. To measure firm undervaluation, the market-to-book (MTB) ratio was used as proposed by Palepu (1986).

The results from the univariate analysis in table 5.1a provide support to the hypothesized relationship as they show that target firms have a substantially lower MTB-ratio compared to non-targets significant at the 1% level. These results are similar to those with e.g. Powell and Yawson (2007) both in terms of mean values and significance.

The multivariate analysis (table 5.1b) further strengthens the hypothesized negative relationship between MTB and takeover likelihood as all models suggest a negative coefficient. Six models report significance at the 1%

level, model E with the 5% level, while model B (nearest neighbor with PSM) is the only one with an insignificant result. These combined suggest that the hypothesis should be confirmed. Therefore, the findings are consistent with theory of firm undervaluation and in line with studies such as Hasbrouck (1985) and Walter (1994).

5.1.5 Growth-Resource Mismatch

The growth resource mismatch hypothesis stipulates that companies with a mismatch between their growth opportunities and resources are likely to become acquisition targets. The hypothesis was introduced by Palepu (1986) and is proxied by a growth-resource mismatch dummy computed by the variables of sales growth, liquidity and leverage. The mismatch is present when a firm has low growth with rich resources and vice versa. This hypothesis was derived and discussed in section 3.1.5.

The univariate analysis (table 5.1a) shows that the growth-resource dummy is insignificant indicating that there is no difference in the growth-resource imbalance between targets and non-targets. This result remains for liquidity and leverage. However, the t-test identifies a significant difference in sales growth showing that targets on average experience lower growth in sales.

The insignificant relationship from the univariate test is validated by the multivariate analysis (table 5.1b), where all models, except model 1C, reject the hypothesis. It is worth pointing out that the negative coefficient of model 1C contradicts the underlying theory behind the hypothesis but is in line with the results of previous studies (see e.g. Ambrose & Megginson, 2003; Espahbodi & Espahbodi, 2003; Danbolt et al., 2016). Espahbodi & Espahbodi (2003) argued that either the underlying theory is incorrect or that the dummy variable (GRD) poorly operationalizes the concept. However, a majority of the multivariate models show significantly that target firms have higher leverage and lower sales growth.

In summary, the growth-resource mismatch hypothesis is rejected as only one model provided a significant coefficient but with the opposite sign. However, the strong evidence for leverage and sales growth might indicate that the underlying theory is not entirely irrelevant, but the proxy poorly operationalizes the concept.

5.1.6 Tangible assets ratio

The tangible assets hypothesis builds on the assumption that bidders are more interested in acquiring firms with a higher ratio of tangible assets. As discussed in section 3.1.6, the underlying theory behind the hypothesis suggests that tangible assets provide a firm financial slack. That is since tangible assets can be used as collateral when raising capital in times of need (e.g. Myers & Majluf, 1984; Stulz & Johnson, 1985). Consequently, it is expected that targets have a higher ratio of tangible assets.

The univariate test (table 5.1a) supports that the mean values between targets and non-targets significantly differ, but the relationship is opposite to the theory. The observed contradiction also opposes the findings of previous studies such as Ambrose & Megginson (1992), Powell (2004) and Danbolt et al. (2016), which all found targets having higher tangible asset ratios relative to non-targets.

The multivariate models (table 5.1b), except model 1C, fail to provide significant results indicating a negligible impact of tangible asset ratio on a firm's takeover likelihood. The estimated coefficients are coherently negative across the models, again opposing the underlying theory and previous studies. The insignificant findings from the multivariate analysis lead to the rejection of the tangible assets hypothesis.

5.1.7 Free cash flow

The free cash flow hypothesis stipulates that free cash flow is positively correlated with a firm's acquisition probability. As presented in section 3.1.7, the hypothesis was initially proposed by Powell (1997). This thesis employed the ratio of cash flow from operations less capital expenses to total assets as a proxy to test this hypothesis.

The results in table 5.1a indicate that the univariate test does not find significance to the free cash flow hypothesis. The result is in line with Powell and Yawson (2007) and Brar et al. (2009), neither of whom found significance for the hypothesis in a univariate test.

The multivariate analysis (table 5.1b), however, provides support for the free cash flow hypothesis. The base model 1A identifies a significant positive relationship at the 1% level, which remains robust when adjusting standard errors for clustering across industry (1F), time (1G) and firm (1H). The significant positive relationship is further supported by model 1D (matching with CEM). Model 1C is the only model with a negative coefficient. Considering all models, the majority of them support the hypothesis, and thus, it is validated. This is in line with the findings of previous studies, which conclude that free cash flow attracts bidders (Powell, 1997; Brar et al., 2009). However, it must be noted that the evidence for validating the hypothesis was neither self-explanatory nor coherent due to significant opposite results from model C (full matching with PSM) and lack of significant support from model B and E, and univariate analysis. Thus, the result is not equally robust compared to other validated hypotheses.

5.1.8 Industry concentration

The industry concentration hypothesis argues that takeover likelihood is more likely to occur in industries with lower market concentration due to antitrust regulation and a more active market for corporate control. The hypothesis was discussed in section 3.1.8 and is proxied by the Herfindahl-Hirschman Index (HHI). The index increases as the number of firms within a specific industry diminish, indicating that the industry has become more concentrated. Takeover likelihood was expected to have a negative relationship with HHI.

As indicated in table 5.1a, the mean values of industry concentration are significantly lower for targets compared to non-targets at the 1% level. These findings are consistent with the t-test conducted by Powell and Yawson (2007) and, to some extent, Brar et al. (2009).

The results from the multivariate analysis (table 5.1b) show that all models, consistent with the theory, find a negative coefficient. However, only model 1C finds slight significance at the 10% level. Despite there seems to be a negative relationship between industry concentration and takeover likelihood, the hypothesis is invalidated due to lack of significance.

5.1.9 Share repurchase

The share repurchase hypothesis is two-folded consisting of two contradicting viewpoints. Hypothesis 9a suggests that share repurchase reduces a firm's takeover likelihood and builds on theories such as free cash flow distribution and takeover defense tactics. Hypothesis 9b, on the other hand, suggests a positive relationship and builds on theories such as managerial signaling. These two hypotheses are contradictory but based on prominent theories from financial literature. The development of both hypotheses was discussed in section 3.1.9.

The univariate analysis (table 5.1a) shows that targets have lower mean values compared to non-target firms indicating a lower level of stock repurchase. The result is significant at the 1% level. Multivariate analysis (table 5.1b) supports the finding by concluding a significant negative relationship between stock repurchase activity and takeover likelihood within three models using matching and the models with robust clustered standard errors. The other models support the negative relationship but could not find significance at the 5% level. Thus, it is concluded that share repurchase decreases takeover likelihood, and the hypothesis 9a is accepted, while 9b is rejected. The inverse relationship between stock repurchase and takeover likelihood is supported by Fama and French (2001) who argue that share repurchases are used for redistributing excess cash flow. Markets generally react positively to such redistribution of free cash flow as they alleviate agency problems (Grullon & Michealy, 2004).

5.1.10 Summary

The table below (5.1.10) summarizes the hypothesis validations. The following hypotheses were concluded as significant and coherent with the theory: inefficient management (both stock return and ROCE), firm size, firm undervaluation and share repurchase. Additionally, leverage and sales growth were shown to have significant impact on the takeover likelihood even though the growth-resource hypothesis was invalidated.

Table 5.1.10 – Significant variables

Hypothesis	Proxy	Validated
Inefficient management	Stock return	Yes
	ROCE	Yes
Firm size	Firm size	Yes
	Revised firm size	No
Firm undervaluation	Market to book	Yes
Growth-resource mismatch	GRD	No
	Leverage	Yes
	Liquidity	No
	Sales growth	Yes
Tangible assets	Tangible assets ratio	No
Free cash flow	Free cash flow ratio	No
Industry concentration	Herfindahl-Hirschman Index (HHI)	No
Share repurchase	Share repurchase dummy	Yes

Notes: This table summarizes the hypothesis validation section. It assesses the results produced by the univariate (Welch t-test) and multivariate analyses (logit regressions) with and without matching. “Yes” indicates that results supported the hypothesis and that it is validated, whereas “No” indicates that the hypothesis could not be validated. The validation criteria is presented and discussed in section 4.3.3.

5.2 Explanatory power of the matching types

This section discusses the explanatory results of the different matching types implemented in this study. The benchmark for the comparison is the multivariate analysis without matching but the explanatory power of the matching types is contrasted to each other as well. Robustness was added to the analysis by reporting the multivariate results of a specific matching type with three different sets of matching variables: (1) year and Ohlson’s O-score, (2) year, O-score and industry, and (3) year and industry. Pseudo R^2 was used as the measure of the explanatory power. As mentioned in the methodology, pseudo R^2 can not be interpreted similarly to regular R^2 in the linear regression, which measures the proportion of variation in the dependent variable explained by the model (Brooks, 2019). Nevertheless, pseudo R^2 increases as the model’s fit increases, and thus, the measure suits the comparison of different model variations.

5.2.1 Full matching

Table 5.2.1: Full matching with PSM

Hypothesis	Proxy	Model A: Year + O-score	Model B: Year + O-score + industry	Model C: Year + industry	No matching
Inefficient management	Stock return (-)	-0,271***	-0,326***	-0,340***	-0,207**
	ROCE (-)	-0,365***	-0,319***	-0,243***	-0,124*
Firm size	Ln Assets (-)	-0,003**	-0,005***	-0,007***	-0,003**
Firm undervaluation	MTB (-)	-0,119***	-0,106***	-0,102***	-0,082***
Growth-resource mismatch	Liquidity ratio (+/-)	-1,119**	1,226***	1,737***	-0,437
	Leverage ratio (+/-)	0,372***	0,007	-0,013	0,172***
	Sales growth (+/-)	-1,012***	-0,799***	-0,745***	-0,385**
	GRM dummy (+/-)	-0,356**	-0,384**	-0,289*	-0,018
Tangible assets	TA ratio (+)	-0,705**	-1,026***	-1,108***	-0,336
Free Cash Flow	FCF (+)	-0,535**	-0,088	1,008***	0,576**
Industry concentration	HH Index (-)	-13590*	-	-	-11800
Share repurchase	SP dummy (-)	-0,907**	-0,650*	-0,650*	-0,968***
Intercept		-3,800***	-4,305***	-4,447***	-3,366***
Pseudo r^2		0,103	0,065	0,065	0,023

Notes: The table represents the results of the logit model where the independent variables are the prediction hypotheses and the dependent variable is the takeover status (target/non-target). Model A is matched with year and Ohlson's O-score; Model B with year, O-score and industry; and model C with year and industry. Stock return is the return from the previous period. ROCE is the return on capital employed. Ln assets is the natural logarithm of total assets. MTB (market to book ratio) is the market value of equity to the book value of equity. Liquidity is the ratio of cash and short term investment to total assets. Leverage ratio is total debt to book value of equity ratio. Sales growth is the change in revenue from the previous period. GRM dummy is the growth-resource mismatch dummy which takes the value 1 if there is a mismatch and 0 otherwise. TA is the ratio of tangible assets to total assets. FCF (free cash flow) is the ratio of operational cash flow stripped of capital investments to total assets. Herfindahl-Hirschman Index (HHI) measures the industry concentration (see section 3.1.8). SP dummy takes the value 1 if there has been a stock repurchase and 0 otherwise. The brackets next to the names represent the hypothesized relationship with takeover likelihood. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

As introduced in the literature review (section 2.5.2), full matching optimally forms subgroups of targets and non-targets from the dataset and provides them weights for improved balance. The multivariate results for the matching type with three sets of matching variables are reported in table 5.2.1. The pseudo R^2 values for full matching with PSM range between 0,065 and 0,103 across the three sets of matching variables as shown in table 5.2.1. Matching with O-score and year (model A) has the best explanatory power, while the two other sets of variables have nearly equal pseudo R^2s. All models find a minimum of eight out of 11 variables significant with the 95% confidence interval. Although most variables are coherent across the models regarding the sign of the coefficient and significances, there are some discrepancies. For free cash flow, model A finds a significant negative coefficient, model B reports the variable very insignificant (p-value 0,737) and model C shows a very significant positive coefficient. Another discrepancy is leverage, which is significant in model A and very insignificant for the other models. The discrepancies indicate that the distribution between targets and non-targets vary within the subclasses depending on the matched variables.

Compared to the multivariate analysis without matching, full matching with PSM has a much higher pseudo R^2 (0,103 versus 0,023) indicating a better explanatory power. Also, from all matching types, full matching with PSM achieves the highest pseudo R^2 across each set of matching variables adding robustness to the superior explanatory performance of that matching type. Full matching with PSM finds more variables to be significant compared to other matching types implying that it is able to find stronger relationships between targets and non-targets within the investigated variables. As full matching divides the observations into optimal subclasses, it may be able to find relationships in these sub-datasets, which other models miss.

The strong explanatory power of full matching with propensity scores in relation to other matching types is contrary to King and Nielsen's (2019) argument of propensity scores' inferior performance. King and Nielsen (2019) criticised PSM's trait of complete randomization in connection to the randomly pruned observations. With full matching, propensity scores are not used to prune observations but to give them weights based on the subclasses, which might partially explain the solid explanatory power. King and Nielsen (2019) also argued that PSM leads to higher model dependence, and thus, higher researcher discretion. In this study, the outcome analysis was implemented by using logit regression for each matching type, and thus, the model dependence and researcher discretion should be minimized in the comparison of the different matching types. Although, this might have been a more considerable problem if only PSM was implemented.

5.2.2 CEM

Table 5.2.2: CEM

Hypothesis	Proxy	Model A: Year + O-score	Model B: Year + O-score + industry	Model C: Year + industry	No matching
Inefficient management	Stock return (-)	-0,148*	-0,168**	-0,165**	-0,207**
	ROCE (-)	-0,044	0,004	-0,123*	-0,124*
Firm size	Ln Assets (-)	-0,001	0,000	-0,001	-0,003**
Firm undervaluation	MTB (-)	-0,071***	-0,074***	-0,084***	-0,082***
Growth-resource mismatch	Liquidity ratio (+/-)	-0,227	-0,480	-0,336	-0,437
	Leverage ratio (+/-)	0,091*	0,102**	0,168***	0,172***
	Sales growth (+/-)	-0,395**	-0,460***	-0,357**	-0,385**
	GRM dummy (+/-)	-0,027	0,095	-0,040	-0,018
Tangible assets	TA ratio (+)	-0,452*	-0,593**	-0,268	-0,336
Free Cash Flow	FCF (+)	0,526**	0,254	0,432*	0,576**
Industry concentration	HH Index (-)	-11760	-	-	-11800
Share repurchase	SP dummy (-)	-0,914**	-0,979***	-1,016***	-0,968***
Intercept		-3,500***	-3,113***	-3,565***	-3,366***
Pseudo r^2		0,004	0,025	0,027	0,023

Note: The table represents the results of the logit model where the independent variables are the prediction hypotheses and the dependent variable is the takeover status (target/non-target). Model A is matched with year and Ohlson's O-score; Model B with year, O-score and industry; and model C with year and industry. Stock return is the return from the previous period. ROCE is the return on capital employed. Ln assets is the natural logarithm of total assets. MTB (market to book ratio) is the market value of equity to the book value of equity. Liquidity is the ratio of cash and short term investment to total assets. Leverage ratio is total debt to book value of equity ratio. Sales growth is the change in revenue from the previous period. GRM dummy is the growth-resource mismatch dummy which takes the value 1 if there is a mismatch and 0 otherwise. TA is the ratio of tangible assets to total assets. FCF (free cash flow) is the ratio of operational cash flow stripped of capital investments to total assets. Herfindahl-Hirschman Index (HHI) measures the industry concentration (see section 3.1.8). SP dummy takes the value 1 if there has been a stock repurchase and 0 otherwise. The brackets next to the names represent the hypothesized relationship with takeover likelihood. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

As introduced earlier, CEM coarsens each variable into intervals and then applies an exact matching algorithm to select the matches and to prune other observations. The multivariate results for CEM models are shown in table 5.2.2. The pseudo R^2 for CEM was stable at around 0.025 for the model B and C but considerably lower for the model A. Thus, it seems that implementing the CEM algorithm with industry as a matching variable had a positive effect on the explanatory power. On the 5% significance level, CEM reported between four and six variables significant, while on the 10% level, all models concluded over half of the variables significant.

Compared to the multivariate model without matching, CEM had slightly higher pseudo R^2, and thus, better explanatory power when the industry was included as the matching variable (models B and C). When industry was not included, the pseudo R^2 was drastically lower than without matching and distinctly the lowest across other matching types with any combination of matching variables. Among the implemented matching types, CEM had the lowest pseudo R^2 with each combination of matching variables indicating the worst explanatory power. CEM reported fewer variables significant compared to the full matching with PSM but more than nearest neighbor approaches. With regards to the variables, CEM produced similar results as multivariate analysis without matching in terms of the sign (positive/negative) of the coefficients and significance of the variables.

The poor explanatory power of CEM relative to other matching types in this study is not in line with Rubin (2006) and Iacus et al. (2011). They argued that MIB class (CEM belongs to) is superior compared to EPBR class (the other matching types belong to) due to the aim to minimize bias instead of variance in the bias-variance tradeoff[14]. As the EPBR methods generated coherently better results, the sampling variance might be a larger source of uncertainty with takeover predictions and it is minimized with EPBR matching methods. As larger variance in the training sample leads the model to be more geared towards that specific dataset, it causes overfitting. EPBR methods are aimed at reducing the variance between targets and non-targets, thus reducing overfitting.

[14] See section 4.2.1.3 for more comprehensive discussion regarding the classification of MIB and EPBR.

5.2.3 - Nearest neighbor with PSM and Mahalanobis distance

Table 5.2.3: Nearest neighbor with PSM and MD

Hypothesis	Proxy	PSM: Model A Year + O-score	PSM: Model B Year + O-score + industry	PSM: Model C Year + industry	MD: Model A Year + O-score	MD: Model B Year + O-score + industry	MD: Model C Year + industry	No matching
Inefficient management	Stock return (-)	-0,243**	-0,263**	-0,128	-0,066	-0,108	-0,158	-0,207**
	ROCE (-)	-0,045	-0,042	-0,119	-0,021	0,034	-0,104	-0,124*
Firm size	Ln Assets (-)	-0,002	-0,003	-0,003	-0,002	0,001	-0,001	-0,003**
Firm undervaluation	MTB (-)	-0,037	-0,092***	-0,098***	-0,081**	-0,066**	-0,088**	-0,082***
Growth-resource mismatch	Liquidity ratio (+/-)	-0,629	-0,329	-0,250	-0,485	0,188	-0,454	-0,437
	Leverage ratio (+/-)	0,238***	0,208**	0,216***	0,079	0,029	0,136*	0,172***
	Sales growth (+/-)	-0,272	-0,458**	-0,374*	-0,527**	-0,540***	-0,409*	-0,385**
	GRM dummy (+/-)	0,008	0,175	-0,085	-0,091	-0,071	0,008	-0,018
Tangible assets	TA ratio (+)	-0,068	-0,446	-0,188	-0,427	0,026	-0,284	-0,336
Free Cash Flow	FCF (+)	0,183	0,749**	0,861**	0,446	0,186	0,281	0,576**
Industry concentration	HH Index (-)	-14490	-	-	-10440	-	-	-11800
Share repurchase	SP dummy (-)	-0,711	-0,874**	-0,736*	-0,940**	-0,927**	-1,150***	-0,968***
Intercept		0,493*	0,798***	0,710**	0,725***	0,075	0,538*	-3,366***
Pseudo r^2		0,034	0,052	0,042	0,033	0,027	0,040	0,023

Note: The table represents the results of the logit model where the independent variables are the prediction hypotheses and the dependent variable is the takeover status (target/non-target). Model A is matched with year and Ohlson's O-score; Model B with year, O-score and industry; and model C with year and industry. Stock return is the return from the previous period. ROCE is the return on capital employed. Ln assets is the natural logarithm of total assets. MTB (market to book ratio) is the market value of equity to the book value of equity. Liquidity is the ratio of cash and short term investment to total assets. Leverage ratio is total debt to book value of equity ratio. Sales growth is the change in revenue from the previous period. GRM dummy is the growth-resource mismatch dummy which takes the value 1 if there is a mismatch and 0 otherwise. TA is the ratio of tangible assets to total assets. FCF (free cash flow) is the ratio of operational cash flow stripped of capital investments to total assets. Herfindahl-Hirschman Index (HHI) measures the industry concentration (see section 3.1.8). SP dummy takes the value 1 if there has been a stock repurchase and 0 otherwise. The brackets next to the names represent the hypothesized relationship with takeover likelihood. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.indicate significance at the 10%, 5% and 1% levels, respectively. Model A, B and C differ on the variables used for matching. Model A is matched with year and Ohlson's O-score; Model B with year, O-score and industry; and model C with year and industry.

1:1 nearest neighbor matches the target with the closest non-target observations measured by either propensity scores or Mahalanobis distance. As shown in table 5.2.3, pseudo R^2 was the highest for model B with PSM as the distance measure. It was nearly twice as high compared to model B with Mahalanobis distance, while the difference was more subtle for models A and C. This indicates the nearest neighbor with PSM having a stronger explanatory power than the Mahalanobis distance. Both distance measures for nearest neighbor matching reported only either two or three significant variables with a 95% confidence interval. The only exception was PSM model B with six significant variables.

Nearest neighbor with both distance measures and each set of matching variables had higher pseudo R^2 compared to the multivariate analysis without matching implying an improved explanatory power. Against other matching types, nearest neighbor with was in the middle; pseudo R^2 of the best model was approximately twice lower compared to the best full matching model (0,101 versus 0,052) and twice higher than the best CEM model (0,052 versus 0,027). Nearest neighbor matching reported notably the lowest amount of variables significant among the matching types.

1:1 nearest neighbor matching has received critique in the previous literature of pruning many observations, and consequently, reducing the explanatory power (Stuart, 2010). On the other hand, Palepu (1986) argued that this matching type would be able to extract meaningful relationships between targets and non-targets due to mitigating the rare-event problem of takeovers. The results from the underlying study can not fully agree nor disagree with either of these arguments. The explanatory power of nearest neighbor matching is worse than full matching, which does not prune observations at all (in line with Stuart) but better compared to CEM, which prunes less observations than nearest neighbor (in line with Palepu).

6. Results: out-of-sample predictions

The previous chapter focused on the explanatory analysis of the takeover likelihood by creating the multivariate models, assessing and understanding the variables affecting the likelihood, and comparing the explanatory power of various models based on different methodological choices. This chapter, contrarily, tests the predictive ability of these models. The predictive ability was tested with the untouched holdout dataset containing observations between 2014-2018. The dataset included 81 target and 6553 non-target observations. In 6.1, the cut-off probabilities are estimated, and in 6.2, the predictive power of various models is examined.

6.1 Estimation of cut-off probabilities

As explained in section 4.4.1, the cut-off point was determined by minimizing the total error in accordance with Palepu (1986). The cut-off point varies for each model and it was defined based on the probability density functions of targets and non-targets in the training sample. To construct the probability density functions, the takeover likelihoods were divided into ten intervals between the minimum and maximum values of the predicted takeover likelihoods. Below, table 6.1a presents the distributions of targets and non-targets in absolute and percentage terms within the ten takeover likelihood intervals for the model without matching.

Table 6.1a: Distribution of estimated acquisition probability – no matching model

Estimated acquisition probability		*Target firms*		*Non-target firms*		
Range	Mid value	Number	$f1(p)$	Number	$f2(p)$	$f1(p)/f2(p)$
0,001 - 0,010	0,005	37	10,5%	5199	22,9%	0,457
0,100 - 0,019	0,014	156	44,1%	11495	50,5%	0,872
0,019 - 0,028	0,023	117	33,1%	4587	20,2%	1,639
0,028 - 0,037	0,032	28	7,9%	1139	5,0%	1,579
0,037 - 0,046	0,041	13	3,7%	237	1,0%	3,524
0,046 - 0,055	0,050	3	0,8%	52	0,3%	3,706
0,055 - 0,064	0,059	0	0%	21	0,1%	
0,064 - 0,073	0,068	0	0%	6	0%	
0,073 - 0,082	0,077	0	0%	3	0%	
0,082 - 0,091	0,086	0	0%	1	0%	
0,091 – 1,000	0,545	0	0%	1	0%	
Total		354	100%	22741	100%	

Notes: The table shows the distributions of targets and non-targets within ten intervals between the minimum and maximum likelihoods. The maximum likelihood is 9,067%. Range represents the interval. Number reports the absolute value of firms within an interval. $f1(p)$ reports the percentage of targets within an interval. $f2(p)$ reports the percentage of targets within an interval. The cut-off point is the value mid value where $f1(p)/f2(p)$ equals 1. It is interpolated from the two nearest $f1(p)/f2(p)$ values around 1. In figure 6.1 the $f1(p)$ and $f2(p)$ values are plotted against the mid value.

Figure 6.1 below plots the probability density functions of targets and non-targets within each takeover likelihood interval for the model without matching. The cut-off probability is the point where the probability density function of targets intersects with non-targets and was calculated as 1,571%[15]. The figure shows that with takeover likelihoods above the cut-off point, the percentage distribution of targets is larger than non-targets while the opposite holds for the likelihoods below the cut-off point. Despite this systematic trend, there is still a sizable overlap between targets and non-targets indicating that the model cannot distinguish targets from non-targets exhaustively.

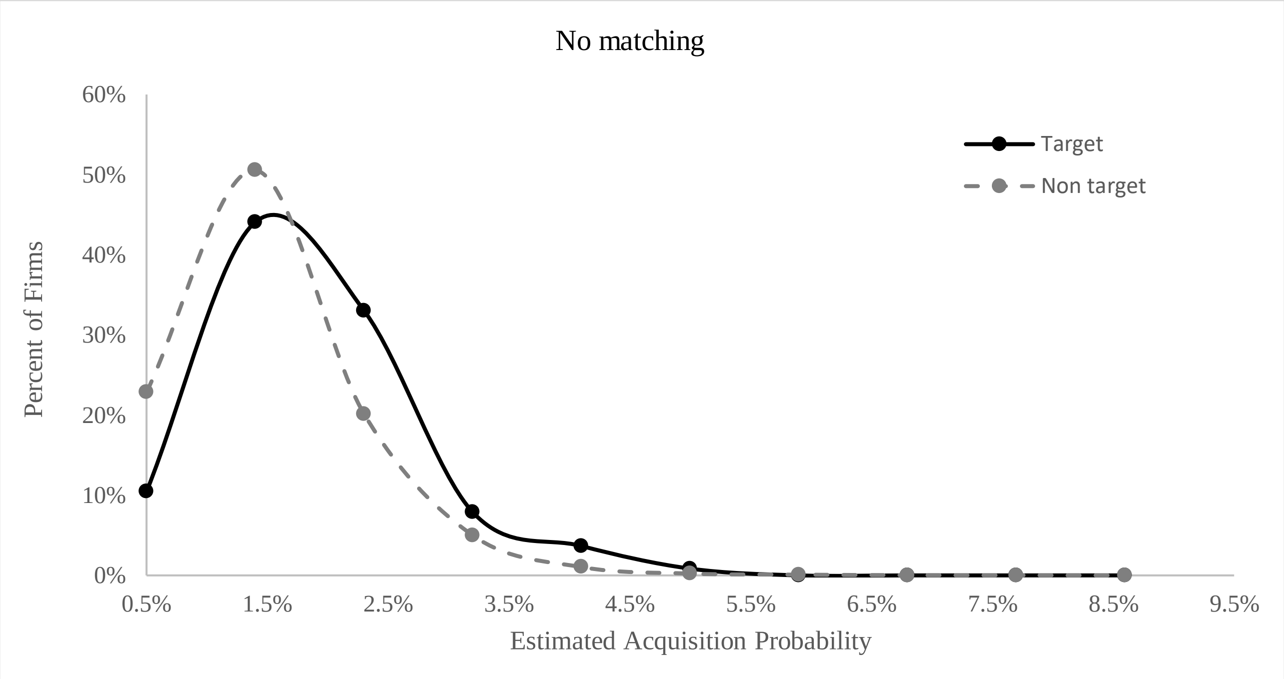

Figure 6.1- Empirical probability density function of acquisition - No Matching

The cut-off probabilities were calculated separately for each model used in the predictions as the cut-off value depends on the takeover likelihood estimations of the specific model. Below in table 6.1b, the cut-off points are presented for the five models with varying matching types. Similar detailed calculations for the cut-off probabilities as above for the no matching model are found in appendix 6.1a-6.1d.

15 The cut-off probability is calculated from the values in table 6.1a. It is the mid value, where f1/f2 equals 1. It is solved via interpolation.

Table 6.1b – Cut-off points for takeover likelihood models

Matching type	Cut-off point
No matching	1,571%
CEM	1,794%
Full matching with PSM	2,615%
Nearest neighbor with PSM	47,673%
Nearest neighbor with MD	47,907%

Notes: The models preprocessed with matching were matched with year and Ohlson's O-score. CEM is coarsened exact matching. PSM is propensity score matching. MD is Mahalanobis distance.

The cut-off probabilities are relatively similar across other matching types except for the two nearest neighbor models, of which cut-off points are substantially higher at nearly 50%. This is mainly due to the distribution between targets and non-targets in the training dataset. The nearest neighbor models are trained with equally balanced datasets between targets and non-targets, while for the other models, a great majority of the dataset consists of non-targets (due to smaller or no pruning of observations). Next, these cut-off points are used to determine whether the predictions on the holdout sample are classified as targets or non-targets.

6.2 Predictive power

Table 6.2a: Out-of-sample prediction test results

	Precision	Recall	Accuracy	TP	TN	FP	FN
No matching	1,66%	41,98%	68,9%	34	4537	2016	47
CEM	1,48%	43,21%	64,2%	35	4224	2329	46
Full matching with PSM	1,73%	46,91%	66,81%	38	4394	2129	43
Nearest neighbor with PSM	1,6%	50,62%	61,44%	41	4035	2518	40
Nearest neighbor with MD	1,6%	49,38%	62,19%	40	4086	2467	41

Notes: The table reports the results from the out-of-sample prediction tests. The reported metrics include precision (TP/TP+FP), recall (TP/TP+FN) and accuracy (TP+TF/TP+TF+FP+FN). TP is the true positive classifications. TN is the true negative classifications. Combined these form the true classifications. FP is the false positive classifications. FN is the false negative classifications. Combined these form the false classifications. The four models preprocessed with matching were matched with year and Ohlson's O-score. CEM is coarsened exact matching. PSM is propensity score matching. MD is Mahalanobis distance.

The predictive power was tested for the five models differing by the matching type employed in the model building. The results from the out-of-sample predictions for these models are presented above in table 6.2a. A simple benchmark for precision is the ratio between targets to all observations as this could be achieved by simply classifying all observations as targets (1,22%). Precision between 1,48% and 1,73%, depending on the prediction model, indicates that the models at least outperform the classification without any predictions. On the other hand, the predictive power is still poor as less than every 50th target prediction is correct. The results from recall confirm the relatively low predictive power of the models; the models are able to predict approximately half of the targets correctly.

Generally, the differences between the models were relatively small with no model clearly standing out in either positive or negative light. Despite the small differences, full matching with PSM reported the strongest results, which was in line with the model's strongest explanatory power among the matching types. The strongest predictive power of full matching with PSM was determined by having the highest precision among the models and having higher values in two out of three performance metrics (precision, recall and accuracy). Also in line with the explanatory analysis, CEM had the lowest predictive power among the matching types with the lowest precision and recall. The model without matching had the highest accuracy with 68.90% but simultaneously a low recall as the model missed the most targets among the models.

The low predictive power with all the models was largely due to the high number of type 2 errors (non-targets misclassified as targets). This finding is in line with the previous research (eg. Powell, 2004; Palepu, 1986; Powell & Yawson, 2007). Type 2 errors indicate that the model assigns high takeover likelihoods for many non-targets, which consequently might indicate that (A) many of the non-targets have similar characteristics with targets and/or (B) the model is not able to distinguish between targets and non-targets due to incorrect methodological choices. (A) The similar characteristics between takeover targets and bankrupted firms were aimed to be controlled by including Ohlson's O-score, a widely-used bankruptcy model introduced in section 3.2.1, as a matching variable. Including O-score for the prediction models did not produce coherent results in relation to the type 2 errors. For two models, the type 2 errors were lower by including O-score as a matching variable, while for two models they were higher. Below in table 6.2b, the type 2 errors are compared between the prediction models (using matching) with two sets of matching variables: year+O-score and year+industry.

Table 6.2b: Type 2 error comparison

	Year + O-score	Year + Industry
Full matching with PSM	2159	2869
CEM	2329	2303
Nearest neighbor with PSM	2518	2294
Nearest neighbor with MD	2647	2482

Notes: The table represents the type 2 errors (= false positives) for the four matching models with two matching variable combinations. CEM is coarsened exact matching. PSM is propensity score matching. MD is Mahalanobis distance.

(B) To account for some of the different methodological choices, the prediction power was tested with multiple matching types and without matching as discussed above. Besides measuring the predictive power with all hypothesized variables, the out-of-sample predictions were implemented with two alternative variable combinations while keeping the matching type constant (the best performing type - full matching with PSM). The alternative variable combinations were the significant variables from the explanatory analysis for full matching with PSM model (5% significance level) and the validated variables based on all models (see table 5.1.10). The prediction results are shown below in table 6.2c. The largest variation occurred for the model with the validated hypotheses, which had the highest accuracy but simultaneously the lowest recall. This was mainly due to cut-off probability having increased from 2,615% to 2,807%. As precision stayed relatively constant, it can be concluded that the predictive capabilities were not impacted a lot.

Table 6.2c: Out-of-sample prediction test results for alternative variable combinations

	Precision	Recall	Accuracy	TP	TN	FP	FN
All Variables	1,73%	46,91%	66,81%	38	4394	2159	43
Significant for full matching with PSM	1,67%	43,21%	68,33%	35	4498	2055	46
Validated samples	1,68%	39,51%	71,07%	32	4683	1870	49

Notes: The table reports the results from the out-of-sample prediction tests for the alternative variable combinations. All three models used full matching with PSM as a matching method and were matched with year and Ohlson's O-score. "All variables" model included: stock return, return on capital employed, Firm size, market-to-book, liquidity, leverage, sales growth, growth-resource dummy (GRD), tangible assets ratio, free cash flow, share repurchase. "Significant variables for full matching with PSM" excluded industry concentration. "Validated variables" excluded GRD, liquidity, tangible assets ratio and industry concentration. The reported metrics include precision (TP/TP+FP), recall (TP/TP+FN) and accuracy (TP+TF/TP+TF+FP+FN). TP is the true positive classifications. TN is the true negative classifications. Combined these form the true classifications. FP is the false positive classifications. FN is the false negative classifications. Combined these form the false classifications.

7. Discussion

7.1 Answers to research questions

Q 1A: Do the widely adopted takeover likelihood hypotheses hold at present? And do other additional variables exist which impact takeover likelihood?

Section 5.1 was dedicated to answering the first research question. All nine takeover likelihood hypotheses were evaluated in that section by conducting both univariate and multivariate analysis. To arrive at robust conclusions regarding the validity of the hypotheses, seven multivariate models were implemented including a base model, four models with different matching types and two models with robust clustered standard errors. These tests indicate that most of the widely adopted takeover likelihood hypotheses hold at present. The tests also indicated that other hypotheses impact the likelihood.

The validated and widely adopted takeover likelihood hypotheses include inefficient management, firm size, firm undervaluation and free cash flow. Additionally, share purchase, sales growth and leverage were shown to impact takeover likelihood. The theoretical arguments in favor of these hypotheses were presented in the hypothesis development section 3.1, except for sales growth and leverage[16]. The remaining hypotheses were accordingly rejected. These include growth-resource mismatch, industry concentration, tangible assets and revised firm size hypothesis. A discussion around the potential reasons to why these hypotheses were not validated is presented below.

The revised firm size hypothesis was not validated. As explained in-depth in section 3.1.3, the hypothesis suggests a concave relationship between takeover likelihood and firm size. While the empirical results of this paper together with the majority of the previous literature concluded the traditional firm size hypothesis valid, some indication for the revised hypothesis was found. The significant positive coefficient for the smallest quintile in the piecewise regression suggests that the relationship is, perhaps, not strictly negative for all firm sizes as previously anticipated. Also, it must be taken into consideration that the sample consisted of only public firms, which tend to be large in size. Thus, the support for the revised relationship might have been strengthened if the sample was not solely limited to public firms.

The lacking empirical support of the growth-resource mismatch was strengthened with this thesis. As mentioned in the hypothesis development section 3.1.5, the results surrounding the validity of this hypothesis have varied substantially across studies (e.g. Palepu, 1986; Ambrose & Megginson, 1992; Powell, 2004;

[16] Sales growth and leverage were implemented as part of the growth-resource mismatch hypothesis. Thus, they did not have a specific theoretical argumentation.

Danbolt et al., 2016). First, the proxy used to identify firms with positive net present value investments can be questioned. The reliance on the revenue growth of the past year might fail to capture the firm's future growth opportunities thus leading to erroneous results. This potential problem was acknowledged also earlier by Palepu (1982). Second, the proxy inherently assumes that all firms with low liquidity and high leverage are expected to be unable to raise funds to finance profitable investment projects. This assumption contradicts the arguments and logic behind Meyer and Majluf's (1981) theory, on which the hypothesis was initially built on (by Palepu, 1986). Instead, Meyer and Majluf (1981) argued that only under certain specific conditions it would be suboptimal for existing shareholders of firms to finance a profitable project with a stock issue. Also, as both sales growth and leverage were significant, a revised version of the growth-resource mismatch might produce interesting results.

The tangible assets hypothesis did not receive empirical support as all models found the opposite relationship between the tangible assets ratio and takeover likelihood. However, most of the models did not find significance aligned with the previous literature (e.g. Powell, 2004). The lack of support for the tangible assets hypothesis was further strengthened by the validation of the undervaluation hypothesis. As mentioned in the hypothesis development section 3.1.6, the underlying theories for these two hypotheses contradict one another. This is because a higher tangible asset ratio is likely to reduce the probability of misvaluation, consequently reducing the likelihood of undervaluation.

Lastly, the industry concentration hypothesis was invalidated due to lack of significance. Although aligned with the theory, each model showed a negative relationship between industry concentration and takeover likelihood. A potential explanation might stem from the employed industry classification, which bundled smaller industries based on SIC codes. As smaller industries are combined with the larger ones, industry dynamics within the smaller industries might become negligible. Thus, to achieve significant results, the industry classification might need to be more granular to better account for the characteristics of smaller industries.

Q 1B: Does statistical matching improve the explanatory power of takeover likelihood model?

Section 5.2 was aimed at answering the second research question. In that section, a total of 12 multivariate models were evaluated (four matching types each with three sets of matching variable combinations) in order to comprehensively test the explanatory power of the different matching types. The three sets of matching variables added robustness to the analysis. Out of the 12 models with matching, 11 outperformed multivariate analysis without matching in terms of the explanatory power measured by pseudo R^2. Seven of these models outperformed the no matching model by more than 50%. Based on these results, it can be concluded that statistical matching does improve the explanatory power of takeover likelihood model.

It was discussed in section 2.5.1 of the literature review that the core objective behind matching is to pre-process data to improve the balance (Ho et al., 2007) between targets and non-targets. The improved balance was consequently linked to improved causal inferences (King and Nielsen, 2019). The causal inferences from the multivariate analysis were indeed improved for the models pre-processed with matching algorithms based on the superior explanatory power. Although the different matching types pre-processed the data using different principles, the results indicate improved balance between targets and non-targets across the matching types.

Despite the coherence among the matching types regarding greater explanatory power against the model without matching, there were differences in comparison to one another. The matching models differed in significant variables and there were some inconsistencies in the signs of coefficients. Interestingly, while full matching with PSM had the highest explanatory power, it also had the most discrepancies against other models in the signs of coefficients. With firm size, full matching with PSM reported a significant negative coefficient for all three models (different sets of matching variables) while the consensus among other models was a positive coefficient. Also, two out of three full matching with PSM models reported opposite signs for liquidity and free cash flow compared to the other models. This contradiction is particularly tricky due to full matching with PSM having the highest explanatory power, thus creating uncertainty of which side to trust - the model with the highest explanatory power or the other three models with coherent results but lower explanatory power. The results between the matching types differ due to matching algorithms function differently in terms of pruning and/or weighting the observations. This leads to different compositions of the dataset, consequently leading to varying results. An important outcome of this discussion is that the employed matching type has a consequential effect on the outcome of the analysis, and therefore, emphasis should be given to the selection process of the matching type. As it might be challenging to motivate the choice of the matching type, multiple types might be applied for added robustness.

Q 2: Does statistical matching improve the predictive performance of takeover likelihood model?

In order to answer the third research question, the predictive performance of the models with and without matching was tested in chapter 6. Unlike explanatory power, the predictive power of the model without matching was in the same vicinity as the models with matching; no matching had the second highest precision, the highest accuracy and the lowest recall among the models. Thus, it can be concluded that statistical matching does not improve the predictive performance of the takeover likelihood model.

Similarly to the explanatory analysis, there were differences among the predictive performance of the matching types. From the first glance, it might be tempting to conclude that all the matching models predicted the takeovers equally inaccurately with, for instance, precision ranging within a 0,25% interval between the models. However, no conclusions can yet be drawn from whether the 0,25% interval is unimportant or not. Simultaneously, the difference in type 2 errors between the models with the highest and lowest precision was 170 observations. For investors, this would entail having invested "falsely" to 170 more targets (which were expected to be targets and generate abnormal returns). Thus, the importance of the differences in the performance measures would depend on the variation in generated profits, and that was not investigated in this thesis. On the other hand, the decision context for managers and policy makers would be different from investors, and thus, the variation in predictive performance might have different consequences for them. Therefore, the differences in predictive performance should, in the end, be assessed in connection with the decision context.

As mentioned in section 6.2, the high number of type 2 errors was a key reason behind the low prediction performance with all models. Ohlson's O-score, risk of bankruptcy measure, was introduced as the matching variable with an aim to reduce the type 2 errors (see section 3.2.1 for in-depth argumentation). While it was found that O-score did not consistently reduce type 2 errors, this thesis did not investigate the resulting type 2 errors further. By including the risk of bankruptcy measure, Ohlson's O-score, the resulting type 2 errors might have included less bankrupt firms compared to not including that as the matching variable.

Explanatory versus predictive power

The results and the consequent answers to the research questions show that matching improves explanatory power but, on the other hand, does not improve predictive power of the model. These two areas of explanatory power and predictive power can be thought of representing different analytical problems; explanatory analysis aims to identify the mechanisms behind the problem at hand while predictive analysis strives to identify the future. The more traditional view of statistics perceived these two problems indistinguishable - looking at the same problem from different angles hypothesizing coherent results among the explanatory and predictive parts of the analysis. The lack of coherence between explanatory and predictive power in the results contradicts the traditional statistics view and supports the clear distinction between explanatory and predictive problems. Consequently, this suggests that while a particular model might succeed in identifying the mechanisms (i.e. the variables affecting takeover likelihood), the same model is necessarily not the optimal choice for understanding the effects of the mechanisms and identifying the future (i.e. predicting the targets from unseen data). The results of this thesis indicate that logit models with matching were able to identify the right mechanisms (although some are still likely to be unknown), but the same models were not able to incorporate the changing effects over time in the holdout sample. Thus, this might suggest treating the explanatory and predictive sides of the analysis separately and applying different methodologies for optimizing the outcome of both.

The separation of explanatory and predictive capabilities of takeovers is relevant for various stakeholders for whom the importance varies between the two areas. As investors are primarily striving to profit from the expected abnormal returns of the takeover targets (Jensen & Ruback, 1983; Andrade et al., 2001), they are mainly concerned with accurate predictions of the targets, while the variables affecting the takeover are not equally important for them. On the other hand, policy makers and regulators are likely to be most interested in the mechanisms increasing the likelihood of takeovers. Understanding the underlying mechanisms would allow them to improve the decision-making regarding takeovers (Powell, 1997). Management might be interested in both - understanding the determinants of takeover likelihood and predicting future takeover activity. By understanding the mechanisms, they could more likely prevent the possible takeover or increase the acquisition price. By accurately predicting the future M&A activity, would allow the managers to enhance their understanding of the industry structure, and thus, better their decision-making.

7.2 Limitations

Generally, the methodological choices are likely to have influenced the outcomes of this study as previous research in the field has pointed out (e.g. Palepu, 1986; Powell, 2001). Often, the promoted methodological improvements from the earlier literature have had a significant influence on the results. A key focus of this research was to focus on the impact of matching to the explanatory and predictive power of takeover likelihood. However, matching is only a part of the methodological choices that are made during the analysis process. Others include, for instance, the definition of the outcome analysis model, analysis variables, train-test split, holdout sample construction and method for cut-off probability. All these other choices, which mainly relied on the previous research in the field, had likely an important influence on the outcome. The other methodological choices might have even had an important influence on the conclusions made regarding matching.

The application of the chosen methodology had its limitations. The holdout sample covered the period of 2014-2018, but for the holdout to be truly out-of-sample, no research should have been used during the sample period. That is because if the takeover model was used to predict the future, no future research would naturally be accessible during the time of model building. In this thesis, we utilized research post-2014, which might have slightly biased the prediction results. A solution for that could have been a shorter holdout period in terms of years. Although, that was not a viable option in this thesis as the number of targets would have been too low for the holdout sample (due to limited access to data as discussed later in this section).

As mentioned in section 7.1, the shortfalls in industry classifications led potentially to invalidating the industry concentration hypothesis. The classifications, similarly, might have biased matching with the industry variable. Additionally, the industry sizes (used in industry concentration hypothesis) were calculated from the existing firms in the sample. As the sample only consisted of public firms, the industry sizes relative to one another do not represent the true sizes due to the lack of private firms. On the other hand, as the public firms tend to be the largest ones of the industry, the industry sizes should still decently represent reality.

Finally, the dataset used in this thesis was affected by the limited data access due to COVID-19[17]. The impact of limited data access was two-folded. Firstly, it affected decision making regarding the research design. Additional variables were hypothesized to impact takeover likelihood but could not be incorporated into the models due to no data access. On the other hand, this led to a stronger focus on the impact of matching to takeover likelihood. Secondly, the limited data access caused the pruning of a large number of observations. Many of the observations lacked data on one or more variables, thus not being qualified for the final dataset. This was especially challenging with targets as they represented a tiny share of the total observations. Without database access, the missing data points were not possible to be filled.

7.3 Future research

Firstly, as it was mentioned in the limitation section, the limited access to data led to omitting variables with a solid theoretical basis for impacting takeover likelihood. One of these was the human resource cost hypothesis. It builds on the notion that value creation through synergies is one of the main motives behind acquisitions. A substantial part of these synergies is realized through the reduction in operational costs (Devos et al., 2009), which in turn predominantly consists of personnel costs (e.g. Shleifer and Summers, 1988). Future research could incorporate the HR-cost hypothesis in the takeover likelihood model. Other new variables are encouraged to be investigated as the literature has not likely found the true variables even after this study.

Although the main focus of this thesis was in evaluating various matching types, it was shown that also the choice of matching variables impacted the outcome, especially in the explanatory analysis. The explanatory power, the sign of coefficient and significance of the variable varied across the models with different sets of matching variables including some inconsistencies within the matching types. Matching variables have received a fairly small amount of attention in the previous literature, and thus, we would encourage future research to investigate the optimal set of matching variables for modelling takeover likelihood.

Thirdly, many of the developed hypotheses behind the takeover likelihood are related to the financial condition of the target firm. This might indicate that the models of this thesis, and in most of the previous literature in the field, are better suited to distinguishing financially motivated takeovers instead of strategic acquisitions.

[17] Coronavirus disease 2019 causing a world-wide pandemic during the time of writing this thesis. Led to severe preventative measures including closure of universities restricting access to the most comprehensive databases (including Thomson Reuters Datastream used in this study).

Thus, the prediction accuracy could possibly be improved by focusing only on the financial takeovers instead of takeovers in its entirety. Future research could investigate this by separating the two.

Finally, as mentioned in the discussion, this study did not investigate the type 2 errors from the predictions further. Thus, it would be interesting for future research to investigate whether the type 2 errors with O-score include less bankrupted firms compared to matching without the measure. This would be in interest especially for investors as it has been shown that the profits from investing according to the takeover likelihood predictions have been eroded by the bankrupted firms (Powell, 2004).

8. Conclusion

The underlying thesis focused on two interrelated areas within takeover likelihood. Firstly, this study strived to improve understanding of factors affecting the takeover likelihood, and secondly, to evaluate the ability to predict takeover targets. The methodology was improved from previous studies within the field by employing and investigating the impact of statistical matching. Four distinct matching types were implemented: CEM, full matching with PSM, nearest neighbor with PSM and nearest neighbor with MD.

Aligned with the two-folded focus of this thesis, the analysis was split into the explanatory and predictive parts. The findings from the explanatory analysis showed that matching improved the explanatory power of the takeover likelihood model coherently across the implemented matching types. On the other hand, the results differed among the matching types in terms of the explanatory power and significant variables. Full matching with PSM reported the highest explanatory power among the matching types but simultaneously had the most discrepancies regarding the significance and sign of the variables. The implication for future research is that emphasis should be laid on matching type selection as it affects the outcomes. Matching was concluded not improving the predictive power of a takeover likelihood model.

Based on the explanatory analysis, nine out of 12 variables were concluded significant and impactful to the takeover likelihood. The significant variables proxied the hypotheses of inefficient management, firm size, firm undervaluation, free cash flow and share repurchase. Additionally, lower sales growth and higher leverage were shown to increase takeover likelihood. Contrarily, hypotheses of growth-resource mismatch, tangible assets ratio and industry concentration were not found significant. Predictive power was found to be relatively low across the models - precision was reported 1,730% at the highest.

The incoherent results between the explanatory and predictive analysis indicate that it might be optimal to treat the two areas separately with distinct methodological choices. The discrepancies in the explanatory and predictive power of matching suggest that logit models with matching are well-suited for investigating the constituents of takeover likelihood but other methodologies might be superior for predicting the future. The findings are relevant for various stakeholders. Managers and policy makers, who are mainly interested in the underlying factors of takeover likelihood, should employ matching in their explanatory models. On the other hand, investors and other groups with pure strive to predict future targets correctly should perhaps investigate other methodological alternatives for more accurate predictions.

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Appendix

Appendix 4.1.1 – Training sample characteristics and industry distribution

SIC code range	Industry	Number of unique firms	Firm year observations	Target firm year observations
0000-0999	Agriculture, Forestry, Fishing	135	243	5
1000-1999	Mining and Construction	602	1 751	23
2000-3999	Manufacturing	3437	10 841	150
4000-4999	Transportation and Public Utilities	896	3 045	37
5000-5999	Wholesale and retail trade	776	2 428	44
6000-6999	Finance, Insurance and Real Estate	0	0	0
7000-8999	Services	1717	4 427	92
9000-9999	Public administration	122	361	3
Total		7685	23 096	354

Notes: The table provides an overview of the industry distribution for the training sample. The industry classification builds on the US Standard Industry Classification scheme and the industry definitions reported by Capital IQ. Total number of unique firms represents all unique firms present in the sample including target firms. The Firm year observations contain all firm year observations including target firm observations. The target firm year observations includes all target firm year observations. The financial firms have been excluded as their ratios would otherwise have distorted the result of the analysis (see Brar et al., 2009; Ouzounis et al., 2009).

Appendix 4.1.2 - Holdout sample characteristics and industry distribution

SIC code range	Industry	Firm year observations	Number of unique firms	Target firm year observations
0000-0999	Agriculture, Forestry, Fishing	88	51	1
1000-1999	Mining and Construction	571	299	11
2000-3999	Manufacturing	3 072	1682	29
4000-4999	Transportation and Public Utilities	978	491	15
5000-5999	Wholesale and retail trade	691	359	11
6000-6999	Finance, Insurance and Real Estate	0	0	0

7000-8999	Services	1 184	684	14
9000-9999	Public administration	50	31	0
Total		6 634	3597	81

Notes: The table provides an overview of the industry distribution for the holdout sample. The industry classification builds on the US Standard Industry Classification scheme and the industry definitions reported by Capital IQ. Total number of unique firms represents all unique firms present in the sample including target firms. The Firm year observations contain all firm year observations including target firm observations. The target firm year observations includes all target firm year observations. The financial firms have been excluded as their ratios would otherwise have distorted the result of the analysis (see Brar et al., 2009; Ouzounis et al., 2009).

Appendix 4.1.4a - Descriptive statistics for the raw training sample

Hypothesis	Normal	min	max	Q25	Q75	median	mean	std	skew
Inefficient management	Stock return	-1,000	19999,000	-0,350	0,354	0,000	2,881	158,262	102,386
	ROCE	-17833,660	51680,000	-0,246	0,506	0,160	2,316	566,788	53,052
Firm size	Ln Assets	0,000	20,345	10,374	14,622	12,711	12,408	3,049	-0,425
Revised firm size	Ln Assets^2	0,000	413,936	107,616	213,809	161,569	163,260	72,803	0,222
Firm undervaluation	MTB	-16722,570	5620,000	0,619	2,763	1,466	0,940	141,849	-72,662
Growth-resource mismatch	Liquidity ratio	0,000	1,000	0,027	0,209	0,084	0,156	0,190	1,937
	Leverage ratio	-36073,710	2238,570	0,052	0,938	0,374	-1,291	244,278	-140,838
	Sales growth	-16,778	2426,000	-0,054	0,221	0,067	1,146	29,955	63,290
	GRM dummy	0,000	1,000	0,000	0,000	0,000	0,181	0,385	1,658
Tangible assets	TA ratio	-0,090	1,282	0,089	0,447	0,216	0,292	0,247	0,871
Free Cash Flow	FCF	-856,000	5248,000	-0,085	0,070	0,014	-0,182	36,240	129,807
Industry concentration	HH Index	0,000	0,115	0,000	0,000	0,000	0,000	0,002	38,434
Share repurchase	SP dummy	0,000	1,000	0,000	0,000	0,000	0,069	0,253	3,402

Matching	O-Score	-105706,456	98898,974	-3,382	0,929	-1,553	-4,081	1276,554	-20,141

Notes: This table presents the descriptive statistics of the independent variables for the raw training sample. Stock return is the return from the previous period. ROCE is the return on capital employed. Ln assets is the natural logarithm of total assets. Ln assets^2 is the natural logarithm of total assets squared. MTB (market to book ratio) is the market value of equity to the book value of equity. Liquidity is the ratio of cash and short term investment to total assets. Leverage ratio is total debt to book value of equity ratio. Sales growth is the change in revenue from the previous period. GRM dummy is the growth-resource mismatch dummy which takes the value 1 if there is a mismatch and 0 otherwise. TA is the ratio of tangible assets to total assets. FCF (free cash flow) is the ratio of operational cash flow stripped of capital investments to total assets. Herfindahl-Hirschman Index (HHI) measures the industry concentration (see section 3.1.8). SP dummy takes the value 1 if there has been a stock repurchase and 0 otherwise. O-score represents the risk of bankruptcy (see section 3.2.1).

Appendix 4.1.4b - Descriptive statistics for the winsorized training sample – 5th and 95th percentile

Hypothesis	Normal	min	max	Q25	Q75	median	mean	std	skew
Inefficient management	Stock return	-0,798	2,081	-0,350	0,354	0,000	0,112	0,698	1,279
	ROCE	-1,991	1,771	-0,246	0,506	0,160	0,048	1,032	-0,477
Firm size	Ln Assets	6,955	16,981	10,374	14,622	12,711	12,440	2,809	-0,262
Revised firm size	Ln Assets^2	48,365	288,343	107,616	213,809	161,569	162,639	68,321	0,114
Firm undervaluation	MTB	-4,161	9,427	0,619	2,763	1,466	1,861	2,844	0,670
Growth-resource mismatch	Liquidity ratio	0,003	0,584	0,027	0,209	0,084	0,148	0,164	1,405
	Leverage ratio	-1,583	3,591	0,052	0,938	0,374	0,584	1,109	0,870
	Sales growth	-0,475	1,150	-0,054	0,221	0,067	0,123	0,358	1,175
	GRM dummy	0,000	1,000	0,000	0,000	0,000	0,181	0,385	1,658
Tangible assets	TA ratio	0,018	0,795	0,089	0,447	0,216	0,289	0,238	0,770
Free Cash Flow	FCF	-1,013	0,169	-0,085	0,070	0,014	-0,081	0,283	-2,234
Industry concentration	HH Index	0,000	0,000	0,000	0,000	0,000	0,000	0,000	3,261
Share repurchase	SP dummy	0,000	1,000	0,000	0,000	0,000	0,069	0,253	3,402
Matching	O-Score	-19,458	36,993	-3,382	0,929	-1,553	0,539	11,269	1,733

Notes: This table presents the descriptive statistics of the independent variables for the winsorized training sample. Stock return is the return from the previous period. ROCE is the return on capital employed. Ln assets is the natural logarithm of total assets. Ln assets^2 is the natural logarithm of total assets squared. MTB (market to book ratio) is the market value of equity to the book value of equity. Liquidity is the ratio of cash and short term investment to total assets. Leverage ratio is total debt to book value of equity ratio. Sales growth is the change in revenue from the previous period. GRM dummy is the growth-resource mismatch dummy which takes the value 1 if there is a mismatch and 0 otherwise. TA is the ratio of tangible assets to total assets. FCF (free cash flow) is the ratio of operational cash flow stripped of capital investments to total assets. Herfindahl-Hirschman Index (HHI) measures the industry concentration (see section 3.1.8). SP dummy takes the value 1 if there has been a stock repurchase and 0 otherwise. O-score represents the risk of bankruptcy (see section 3.2.1).

Appendix 4.3.4 – Spearman correlation matrix

	Stock return	ROCE	Ln Assets	Ln Assets^2	MTB	Liquidity ratio	Leverage ratio	Sales growth	GRM dummy	TA ratio	FCF	HH Index	SP dummy
Stock return	1												
ROCE	0,1	1											
Ln Assets	0,01	0,47	1										
Ln Assets^2	0,13	0,09	0,18	1									
MTB	0,04	-0,17	-0,18	0,13	1								
Liquidity ratio	0	0,06	0,3	0,44	-0,19	1							
Leverage ratio	0,18	0,04	-0,03	0,06	0,04	0	1						
Sales growth	0,03	-0,08	-0,06	0,06	0,32	0,03	0,08	1					
GRM dummy	-0,01	0,12	0,24	-0,05	-0,36	0,18	0	-0,08	1				
TA ratio	0,04	0,61	0,57	0,18	-0,18	0,22	-0,03	-0,06	0,09	1			
FCF	-0,01	0,16	0,47	0,06	-0,09	0,1	-0,02	-0,05	0,06	0,15	1		
HH Index	0,01	0,44	0,56	0,16	-0,19	0,29	-0,03	-0,06	0,24	0,52	0,52	1	
SP dummy	0,02	0,15	0,15	0,08	0,01	0,01	-0,02	-0,01	-0,03	0,13	0,05	0,14	1

Notes: This table presents the bivariate (Pearson) correlation coefficients between the independent variables. All coefficients are below the threshold of 0,7, suggested by Dormann et al., 2013), and predominantly of low values wherefore it is unlikely to lead to any problems with multicollinearity. Stock return is the return from the previous period. ROCE is the ratio of EBITDA to total capital employed. Ln assets is the natural logarithm of total assets. Ln assets^2 is the natural logarithm of total assets squared. MTB (market to book ratio) is the market value of equity to the book value of equity. Liquidity is the ratio of cash and short term investment to total assets. Leverage ratio is total debt to book value of equity ratio. Sales growth is the change in revenue from the previous period. GRM dummy is the growth-resource mismatch dummy which takes the value 1 if there is a mismatch and 0 otherwise. TA is the ratio of tangible assets to total assets. FCF (free cash flow) is the ratio of operational cash flow stripped of capital investments to total assets. Herfindahl-Hirschman Index (HHI) measures the industry concentration (see section 3.1.8). SP dummy takes the value 1 if there has been a stock repurchase and 0 otherwise.

APPENDIX 5.1.3: Multivariate regression with revised firm size hypothesis

Hypothesis	**Proxy**	**1I: revised firm size**
Inefficient management	Stock return (-)	-0,2056**
	ROCE (-)	-0,1329*
Firm size	Ln Assets (+)	0,8623***
Revised firm size	Ln Assets^2 (-)	-0,03866***
Firm undervaluation	MTB (-)	-0,09081***
Growth-resource mismatch	Liquidity ratio (+/-)	-0,6016
	Leverage ratio (+/-)	0,1595***
	Sales growth (+/-)	-0,4089**
	GRM dummy (+/-)	-0,02739
Tangible assets	TA ratio (+)	-0,345
Free Cash Flow	FCF (+)	0,1295
Industry concentration	HH Index (-)	11,61
Share repurchase	SP dummy (-)	-0,009647***
Intercept		-3,3661***

Notes: The table represents the results of the logit model where the independent variables are the prediction hypotheses and the dependent variable is the takeover status (target/non-target). Compared to the previous logit models (1A-1H), this model incorporates the revised firm hypothesis into the regression (Ln (Assets)^2). Stock return is the return from the previous period. ROCE is the ratio of EBITDA to total capital employed. Ln assets is the natural logarithm of total assets. Ln assets^2 is the natural logarithm of total assets squared. MTB (market to book ratio) is the market value of equity to the book value of equity. Liquidity is the ratio of cash and short term investment to total assets. Leverage ratio is total debt to book value of equity ratio. Sales growth is the change in revenue from the previous period. GRM dummy is the growth-resource mismatch dummy which takes the value 1 if there is a mismatch and 0 otherwise. TA is the ratio of tangible assets to total assets. FCF (free cash flow) is the ratio of operational cash flow stripped of capital investments to total assets. Herfindahl-Hirschman Index (HHI) measures the industry concentration (see section 3.1.8). SP dummy takes the value 1 if there has been a stock repurchase and 0 otherwise. The brackets next to the proxy names represent the hypothesized relationship with takeover likelihood. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. Model A, B and C differ on the variables used for matching. Model A is matched with year and Ohlson's O-score; Model B with year, O-score and industry; and model C with year and industry.

Appendix 6.1a – Distribution of estimated acquisition probability - CEM

Estimated acquisition probability		*Target firms*		*Non-target firms*		
Range	Mid value	Number	$f1(p)$	Number	$f2(p)$	$f1(p)/f2(p)$
0,002-0,008	0,005	7	2,0%	1405	7,1%	0,278
0,008-0,013	0,010	43	12,1%	3800	19,2%	0,632
0,013-0,019	0,016	105	29,7%	7018	35,5%	0,836
0,019-0,024	0,022	123	34,7%	5267	26,6%	1,305
0,024-0,030	0,027	48	13,6%	1752	8,9%	1,531
0,030-0,035	0,033	22	6,2%	414	2,1%	2,970
0,035-0,041	0,038	4	1,1%	96	0,5%	2,329
0,041-0,046	0,044	2	0,6%	16	0,1%	6,986
0,046-0,052	0,049	0	0,0%	13	0,1%	
0,052-0,058	0,055	0	0,0%	2	0,0%	
0,058-0,063	0,060	0	0,0%	1	0,0%	
Total		354	100%	19784	100%	

Notes: The table shows the distributions of targets and non-targets within ten intervals between the minimum and maximum likelihoods. The maximum likelihood is 5,76% Range represents the interval. Number reports the absolute value of firms within an interval. $f1(p)$ reports the percentage of targets within an interval. $f2(p)$ reports the percentage of targets within an interval. The cut-off point is the value mid value where $f1(p)/f2(p)$ equals 1. It is interpolated from the two nearest $f1(p)/f2(p)$ values around 1. In figure 6.1a the $f1(p)$ and $f2(p)$ values are plotted against the mid value.

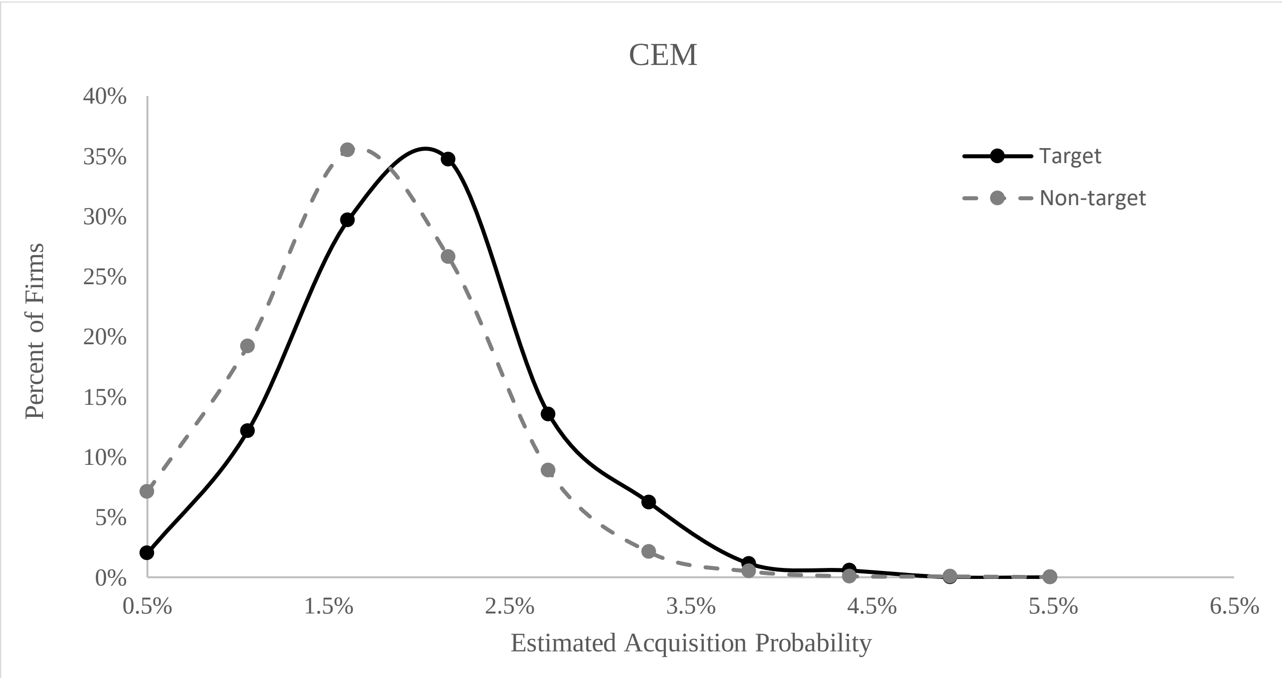

Figure 6.1a Empirical probability density function of acquisition - CEM

Appendix 6.1b –Distribution of estimated acquisition probability – Full matching PSM

Estimated acquisition probability		*Target firms*		*Non-target firms*		
Range	Mid value	Number	$f1(p)$	Number	$f2(p)$	$f1(p)/f2(p)$
0,000-0,036	0,018	230	65,0%	18156	80,4%	0,808
0,036-0,072	0,054	91	25,7%	3465	15,3%	1,676
0,072-0,108	0,090	19	5,4%	688	3,0%	1,762
0,108-0,144	0,126	10	2,8%	200	0,9%	3,191
0,144-0,180	0,162	3	0,8%	58	0,3%	3,301
0,180-0,216	0,198	0	0,0%	9	0,0%	0,000
0,216-0,252	0,234	0	0,0%	3	0,0%	0,000
0,252-0,288	0,270	1	0,3%	6	0,0%	10,635
0,288-0,324	0,306	0	0,0%	2	0,0%	
0,324-0,359	0,341	0	0,0%	1	0,0%	
0,359-0,395	0,377	0	0,0%	1	0,0%	
Total		354	100%	22 589	100%	

Notes: The table shows the distributions of targets and non-targets within ten intervals between the minimum and maximum likelihoods. The maximum likelihood is 35,9%. Range represents the interval. Number reports the absolute value of firms within an interval. $f1(p)$ reports the percentage of targets within an interval. $f2(p)$ reports the percentage of targets within an interval. The cut-off point is the value mid value where $f1(p)/f2(p)$ equals 1. It is interpolated from the two nearest $f1(p)/f2(p)$ values around 1. In figure 6.1b the $f1(p)$ and $f2(p)$ values are plotted against the mid value.

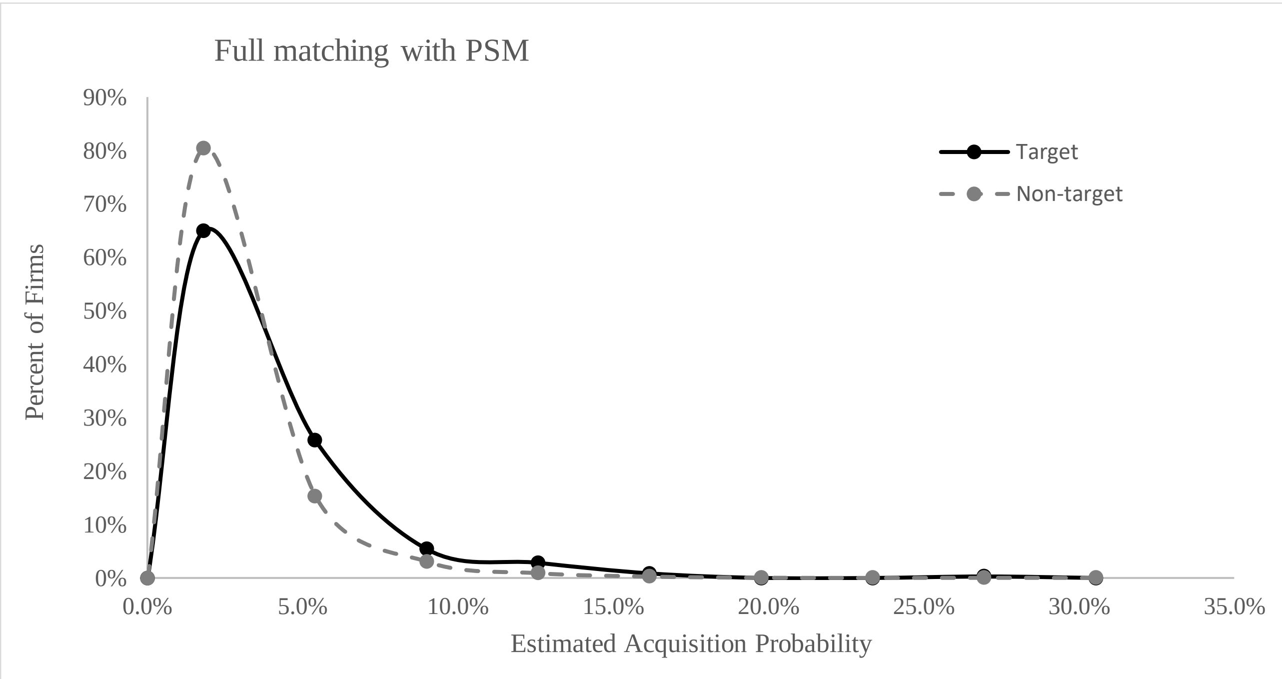

Figure 6.1b Empirical probability density function of acquisition - Full matching PSM

Appendix 6.1c – Distribution of estimated acquisition probability – Nearest neighbour with PSM

Estimated acquisition probability		*Target firms*		*Non-target firms*		
Range	Mid value	Number	$f1(p)$	Number	$f2(p)$	$f1(p)/f2(p)$
0,146-0,208	0,177	0	0,0%	3	0,8%	0,000
0,208-0,271	0,240	2	0,6%	15	4,2%	0,133
0,271-0,333	0,302	16	4,5%	23	6,5%	0,696
0,333-0,395	0,364	19	5,4%	31	8,8%	0,613
0,395-0,458	0,427	46	13,0%	65	18,4%	0,708
0,458-0,520	0,489	89	25,1%	83	23,4%	1,072
0,520-0,583	0,551	90	25,4%	79	22,3%	1,139
0,583-0,645	0,614	47	13,3%	44	12,4%	1,068
0,645-0,707	0,676	31	8,8%	8	2,3%	3,875
0,707-0,770	0,739	13	3,7%	3	0,8%	4,333
0,770-1	0,885	1	0,3%	0	0,0%	
Total		354	100%	354	100%	

Notes: The table shows the distributions of targets and non-targets within ten intervals between the minimum and maximum likelihoods. The maximum likelihood is 76,99%. Range represents the interval. Number reports the absolute value of firms within an interval. $f1(p)$ reports the percentage of targets within an interval. $f2(p)$ reports the percentage of targets within an interval. The cut-off point is the value mid value where $f1(p)/f2(p)$ equals 1. It is interpolated from the two nearest $f1(p)/f2(p)$ values around 1. In figure 6.1c the $f1(p)$ and $f2(p)$ values are plotted against the mid value.

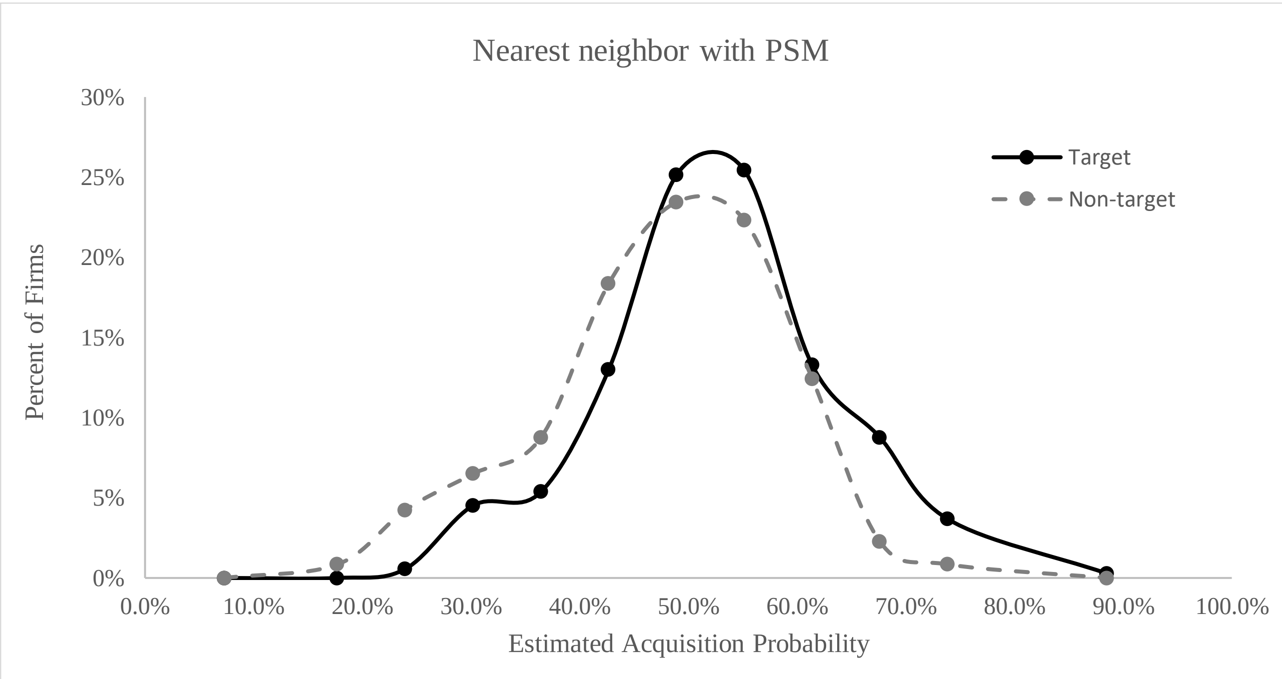

Figure 6.1c Empirical probability density function of acquisition - Nearest neighbor PSM

Appendix 6.1d – Distribution of estimated acquisition probability – Nearest neighbour with MD

Estimated acquisition probability		*Target firms*		*Non-target firms*		
Range	Mid value	Number	$f1(p)$	Number	$f2(p)$	$f1(p)/f2(p)$
0,152-0,214	0,183	1	0,3%	7	2,0%	0,143
0,214-0,276	0,245	6	1,7%	14	4,0%	0,429
0,276-0,337	0,306	10	2,8%	20	5,6%	0,500
0,337-0,339	0,368	19	5,4%	39	11,0%	0,487
0,399-0,461	0,430	36	10,2%	66	18,6%	0,545
0,461-0,523	0,492	85	24,0%	76	21,5%	1,118
0,523-0,585	0,554	110	31,1%	73	20,6%	1,507
0,585-0,646	0,615	61	17,2%	40	11,3%	1,525
0,646-0,708	0,677	24	6,8%	17	4,8%	1,412
0,708-0,770	0,739	2	0,6%	1	0,3%	2,000
0,770-0,832	0,801	0	0,0%	1	0,3%	
Total		354	100%	354	100%	

Notes: Notes: The table shows the distributions of targets and non-targets within ten intervals between the minimum and maximum likelihoods. The maximum likelihood is 76,99%. Range represents the interval. Number reports the absolute value of firms within an interval. $f1(p)$ reports the percentage of targets within an interval. $f2(p)$ reports the percentage of targets within an interval. The cut-off point is the value mid value where $f1(p)/f2(p)$ equals 1. It is interpolated from the two nearest $f1(p)/f2(p)$ values around 1. In figure 6.1d the $f1(p)$ and $f2(p)$ values are plotted against the mid value.

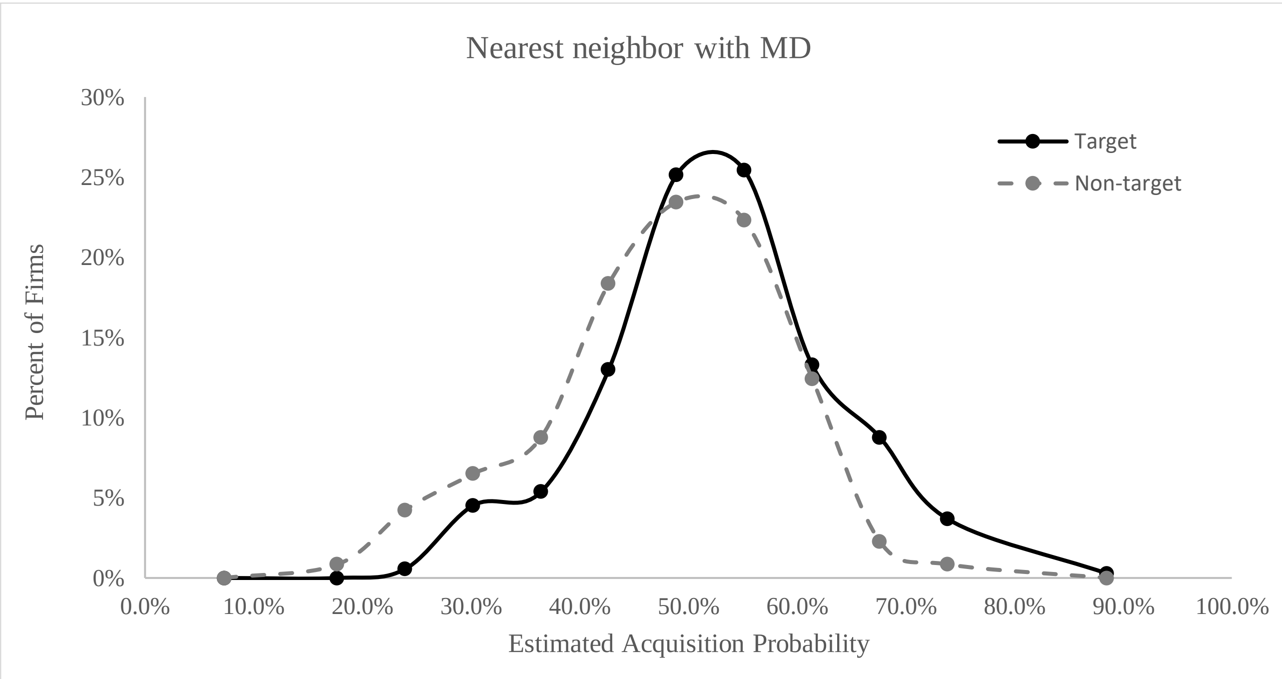

Figure 6.1d- Empirical probability density function of acquisition - Nearest neighbor MD