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A Comparative Study of Logistic Regression and Machine Learning to Identify Acquirer Success Factors

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Undertaking this paper has been a demanding yet fulfilling experience. Our thesis has required rigorous pre-processing and cleaning of a large dataset, as well as embracing state-of-the-art analytic tools. Our hope is that this paper can contribute to the literature on M&A research by employing novel machine learning techniques to address the current limitations of the field.

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Abstract

This paper develops, presents and tests two research questions that contribute to current explanations of shareholder wealth creation in mergers and acquisitions transactions. We (1) identify pre-acquisition success factors and (2) evaluate their practical usefulness for managers seeking to acquire other firms. We build on Cartwright and Schoenberg (2006)'s framework for understanding the persistent failings of acquisitions. This includes agency problems, research not reaching practitioners and the need for new methods to explain M&A success. Our findings indicate that financial ratios play a significant role in determining the success of acquirers. We develop and validate both a logistic regression and two machine learning models, revealing significant factors that impact acquirer success.

Our results from the logistic regression mirror those from much of existing literature, identifying several significant factors for acquirer success. Furthermore, we find support for the prevalence of agency problems in acquisition decisions (Jensen, 1986; Maloney et al., 1993) and the internal market hypothesis (Stein, 1997; Shin and Stulz, 1998). Yet, our results also conflict with existing literature on several points. While our logistic regression reveals statistically significant acquirer success factors, its poor predictive performance makes it impractical for managers in real-world applications. In contrast, our machine learning methods identify complex non-linear relationships and discriminates well between successful and unsuccessful acquirers, resulting in ROC curves with excellent AUC scores. This supports the argument that the true relationships between acquirer success and the predictors are too complex for a logistic regression approach, even though much of existing literature on the subject builds on the logistic regression. We thus provide a possible explanation for why M&A success rates are still low, despite the extensive research on the subject. Finally, we argue that the key to enabling managers to use machine learning models directly lies in the adoption of partial dependence plots, as they facilitate a deeper understanding of the models and lets managers explain them to stakeholders more easily.

Keywords – Acquisitions, M&A, Machine learning, Partial Dependence Plots, Random Forest, Gradient Boosting Machine, Agency theory

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1 Introduction

Despite the high historical failure rate of mergers and acquisitions (King et al., 2004), the value of M&A deals remains consistently high and peaked at a record $5,900 billion globally in 2021 (Bain&Company, 2023), perpetually captivating the interest of researchers and practitioners alike. Since the pessimistic meta-studies by King et al. (2004) and Cartwright and Schoenberg (2006), there has been a large development in available analytic tools for empirical researchers. This change not only revolutionized the methods available, but also elevated the ambition level of many researchers, now hoping to predict M&A success with far higher accuracy than before.

Two studies aiming to identify factors leading to M&A success are performed by Alhenawi and Stilwell (2017) and Leepsa and Chandra (2017). Both studies find a group of financial ratios which are significantly associated with M&A success, thus arguing for pre-acquisition financial ratios as a measure of acquisition competency. The studies measure success by whether the merger or acquisition created shareholder value[1]. By demonstrating a significant association between pre-merger financial ratios and M&A success, these studies emphasize the crucial role of financial ratios in assessing acquisition competency and creating shareholder wealth. Our thesis falls into the same category, but with less focus on prediction accuracy for its own sake, rather looking for the managerial implications from the models we explore. Furthermore, our approach and methods differ from traditional M&A research as we do not focus solely on assessing the match between the acquirer and acquisition target for value creation. Much of the existing literature uses vague terms like culture-fit and cultural compatibility to define a good match between firms, making them difficult for practitioners to apply (Cartwright and Schoenberg, 2006). Instead, we aim to evaluate whether a firm is suited to acquire other firms, as we consider it a critical initial step prior to analyzing compatibility. I.e., we examine which firms *should* acquire others, instead of focusing on whether two firms are a good match.

The widely referenced meta-analysis of post-M&A performance by King et al. (2004), examining hundreds of studies, concluded that there is still a need for theory development and that current research methods were not sufficient. This is echoed by Cartwright and

[1] Alhenawi and Stilwell (2017) measure this by positive CAR, while Leepsa and Chandra (2017) measure it by positive EVA-rate.

Schoenberg (2006), pointing to M&As still failing despite a growing body of research. They attribute the failings to (1) that "executives are undertaking acquisitions driven by non-value maximizing motives" (Jensen, 1986; Gibbons and Murphy, 1992; Hyland and Diltz, 2002; Aggarwal and Samwick, 2003), (2) "the prescriptions from the academic research not reaching the practitioner community" and (3) "the research to date is incomplete in some way". This thesis aims to identify the reasons behind the persistent failings and propose new methods to address them. Our study makes use of partial dependence plots, a novel technique for analyzing the previously black box relationships within machine learning models. Additionally, variable importance plots are used. Together, they providing insight into both the importance and direction of these relationships. Our view is that partial dependence plots are a pivotal factor in enabling future M&A research to use machine learning methods where logistic regression was formerly used.

Given the aforementioned failings, we believe there is an opportunity for machine learning to provide new insight to managers contemplating an acquisition. As such, we propose that the continued failing of M&As might also come as a result of empirical research not taking the position of the manager into account. While much research has focused on the interest conflict between managers and stakeholders, not much thought has been given to how applicable the results from the research are for the average manager. Therefore, this thesis contends that the existing knowledge gap between empirical research and the practical needs of managers contributes to the persisting failings of M&As, as managers lack access to relevant insights that can inform their decision-making. Hence, this thesis proposes to investigate the potential of machine learning to bridge this gap and facilitate the translation of research findings into actionable guidance for managers.

With this in mind, our goal is to (1) determine pre-acquisition success[2] factors and (2) determine the usefulness of the results for managers to identify whether their company is positioned for acquisition success. The first goal is investigated by identifying statistically significant variables from logistic regression, and partial dependence plots and variable importance plots from machine leaning models. The second goal is investigated by the use of ROC curves and their respective AUC values to measure the predictive performance of

[2]We measure acquirer success as a binary variable which is 1 if the acquirer achieves a positive cumulative abnormal return after the acquisition takes place, and 0 otherwise. A formal definition is given in section 4.

each machine learning model.

The structure of this thesis is as follows. Chapter 2 contains a literature review and the development of our research questions. Chapter 3 contains the process of obtaining, cleaning and merging our data sample from multiple data sources. This chapter also contains construction of dummy variables related to acquisitions, as well as the calculation of cumulative abnormal return and its constituents. Descriptive statistics for the variables used in our analysis are also located here. Chapter 4 introduces our financial measures of performance, as well as explaining how we measure acquisition success. The analytic models used in the thesis as well as their validation and interpretation are also outlined here. Next, chapter 5 outlines the results from the logistic model, random forest model and gradient boosting machine, and an analysis of the implications of the findings with regards to our research questions. The models are also compared, both with regards to predictive power and managerial applicability. In chapter 6 we perform model validation and discuss the implications of the different models in the context of extant literature and managerial application. Challenges and limitations of our thesis are also explored in this chapter. Finally, chapter 7 concludes our results in the light of our research questions.

2 Background

This thesis builds on the framework proposed by Cartwright and Schoenberg (2006) to address the persistent failings of M&As:

1. Agency problems - Do managers prioritize shareholder wealth in acquisitions?
2. Research not reaching practitioners - Is the research not reaching the managers or not being adopted for other reasons?
3. A need for new methods, theories and variables to explain M&A success - Can the unexplained variance in M&A success be explained?

In the following sections, we will analyze these points in detail and review relevant literature from the past few decades to provide a comprehensive overview of the current state of M&A research and its connection to our research questions.

2.1 Agency problems in acquisitions

This first explanation of M&A failure is best illustrated by Adam Smith (1776) in The Wealth of Nations:

"The directors of such [joint-stock] companies, however, being the managers rather of other people's money than of their own, it cannot well be expected, that they should watch over it with the same anxious vigilance with which the partners in a private copartnery frequently watch over their own."

In the widely cited article by Jensen and Meckling (1976), which we adopt to our thesis, agency costs are defined as the costs generated as the shareholder engages the manager to manage the firm on their behalf, which involves delegating some decision making authority to the manager. The manifestation of agency costs in acquisitions is observed by Seth et al. (2000), which in cross-border US acquisitions find that 26% of the activity was sparked by managers expected utility and not in the interest of creating shareholder value. These findings establish the first explanation as plausible, but before looking at more of the nuances and motivations, we take a step back and look at acquisitions from the shareholder perspective.

2.1.1 Do acquisitions create shareholder value?

The extant literature on whether acquisitions create shareholder value is dichotomous. On one hand, several studies have documented that M&A transactions can destroy value for the acquirer's shareholders, while other evidence support the opposite. An article by Dos Santos et al. (2008) shows that corporate international diversification through acquisitions of unrelated firms result in a reduction of shareholder value because of a diversification discount of about 24%. However, acquisitions of related firms did not induce a discount (Dos Santos et al., 2008). Cole and Vu (2006) find that contrary to the synergies hypothesis, horizontal mergers[3] realize the greatest *negative* cumulative abnormal returns. Additional reasons for value-destroying acquisitions include disproportionately avoiding private targets (Harford et al., 2012) and contagion/capacity effects (Shaver, 2006). The consensus view is that acquisitions generally create value for the target firm's shareholders, while investors in the bidding firm experience share price under-performance in the months following the acquisition (King et al., 2004; Agrawal and Jaffe, 2000). Managers of acquiring firms report that only 56% of their own acquisitions are considered successful in achieving the objectives they set out achieve (Cartwright and Schoenberg, 2006). Things also tend to get messy on the target side, with almost 70% of target firm executives departing within five years following the acquisition (Krug and Aguilera, 2005).

One reason for the failure of M&As to create shareholder value are the challenges of managing diversity within a company. Rajan et al. (2000) argue that a diverse set of divisions within a company can lead to political battles over resource allocation, and distortions in investment decisions. These distortions can lead to inefficiencies and hence, a reduction in shareholder value. Moreover, the study suggests that the introduction of a new subunit in a hierarchy can have ramifications for other subunits, even when there is no operational link between them. This is because the change alters the power structure in the hierarchy and affects decision-making processes, again leading to inefficiencies. This implies that when an acquisition brings in a new subunit, it can reduce shareholder value by making the firm more inefficient.

Additionally, Rajan et al. (2000) suggest that spin-offs that reduce diversity tend to add value, indicating that companies with excessive diversification may benefit from

[3] Mergers between competing firms, as opposed to up or down the supply chain.

being broken up. The implications of this finding for companies considering a diversity-increasing acquisition are significant, as it suggests that such a process may ultimately erode shareholder value. Based on the findings by Rajan et al. (2000), it appears organizational complexity can reduce the company's ability to generate shareholder value. Assuming that acquisitions increase organizational complexity, this is a reason for why acquisitions often destroy value.

2.1.2 Why do managers initiate acquisitions?

The goal for acquisition activity is usually thought of as firms seeking higher performance (Bergh, 1997) and economies of scale and scope, market power and learning (Hitt et al., 2001). Extant literature indicates that most acquisitions are initiated to meet these goals. The decision to acquire may be driven by a firm seeking efficiency (Bailey and Friedlaender, 1982) or overcoming entry barriers (Chang and Rosenzweig, 2001). According to Jensen (1988), the market for corporate control is generating substantial benefits for shareholders and for the economy as a whole by loosening control over vast amounts of resources and enabling them to move more swiftly to their most valuable use. The motivation for managers to initiate acquisitions can thus be seen as a way to create shareholder value by increasing firm performance.

Circling back to the agency problems, further studies argue that some acquisitions are primarily initiated as a result of manager self-interest. According to Trautwein (1990), the theories that attribute acquisitions to managerial empire-building or private information are supported by stronger empirical evidence compared to theories that link mergers to efficiency gains or market power. Gaughan (2003) points to a wave of large, failed M&A deals, blaming empire-building CEOs unrestrained by lazy boards of directors. These problems have spawned a branch of private equity funds which target firms that engage in empire building, creating value by shedding the previously acquired firms (Gantchev et al., 2020). This fund strategy has been successful in increasing the returns of divested firms (Gantchev et al., 2020), implying that these firms should not have been acquired in the first place. In general, one of the most significant challenges facing M&As is the frequent occurrence of deals between companies that are poorly suited to merge or acquire one another, resulting in sub-optimal outcomes for all parties involved.

2.2 Is M&A research reaching the practitioner?

While the agency problem is a well-established issue in M&A research, the related issue of practitioners not being able to access or apply the results of empirical research has received comparatively little attention, despite the enormous volume of M&A activity worldwide (Bain&Company, 2023). However, the issue of research not reaching practitioners may be more a result of research findings not being practical enough, rather than the absence of advice. While much research has explored the relationship between managerial expertise and M&A performance (King et al., 2004), little attention has been paid to the specific knowledge of M&A strategy that managers possess and its impact on acquisition success. The absence of research on the connection between manager competence and M&A performance may be partly due to the inherent difficulty of assessing manager competence with accuracy. The findings of Rosenzweig (1993) suggest that experience in M&A and strategic management are crucial components of successful acquisitions, reinforcing the need for managers to have expertise in these areas. Another important issue highlighted in M&A research is the over-commitment to deteriorating deals, which can be driven by personal incentives (Hayward and Hambrick, 1997). This highlights the potential conflict of interest between the managers and shareholders in M&A transactions, and the importance of aligning these interests. If managers lack research-backed methods of performing successful acquisitions and shareholders are not able to evaluate the quality of these decisions, it is unsurprising that shareholder wealth continues to be destroyed.

Another challenge in the field of M&A research is the wide spectrum of variables observed to have an effect of successful mergers (Cartwright and Schoenberg, 2006). This encourages researchers to perform studies in the hope of finding the magic pill, especially now with machine learning algorithms being able to find connections where none seem to exist in a logistic regression. While increasing the amount of variables on the spectrum observed might improve the predictive power of the model, the resulting implications for managers become more complex and impractical. Historically, M&A research has followed disciplinary lines (Cartwright and Schoenberg, 2006), but by only focusing on a few traditionally accepted financial variables, one might miss the crucial levers of success in a particular case. Researchers thus face a trade-off between casting a wide net to identify a range of potentially significant variables, or focusing on a smaller set of variables to ensure the practicality and usability of their findings for practitioners.

2.3 The quest for new theory, methods and variables

The last explanation of current M&A failures by Cartwright and Schoenberg (2006) is that current research methods are incomplete in some way or form. In this section, we examine theory, methods and variables for acquisitions success in the extant literature. Further adding to the motivation for this part is the quote from King et al. (2004): "our results indicate that post-acquisition performance is moderated by variables unspecified in existing research [...]. An implication is that changes to both M&A theory and research methods may be needed" (King et al., 2004). Finally, the meta analysis by Stahl and VOIGHT (2004) looking at the significance of culture on post-acquisition performance concluded that "a huge portion of variance remains unexplained" (Stahl and VOIGHT, 2004). As we continue our review, we start by looking at the financial and strategic factors for acquisition success, with the above explanation from Cartwright and Schoenberg (2006) in mind. Additionally, we briefly review the findings of behavioral studies, as viewed through the lens of Stahl and VOIGHT (2004).

2.3.1 Which factors impact acquisition success?

Identifying the success factors of an acquisition is essential for companies seeking to acquire another company. A study by Leepsa and Chandra (2017) uses logistic regression to determine which factors increase the odds of a merger or acquisition being successful, measured by a positive post-M&A EVA rate[4]. The study reveals that pre-M&A quick ratio and asset turnover ratio exhibit a positive correlation with M&A success, while pre-M&A current ratio and net profit margin have a negative association. These financial ratios are defined in section 4. Of these factors, quick ratio was the most significant. Leepsa and Chandra (2017) conclude that managers "should give more importance to a company's liquidity position". However, the predictive performance of the model is weak as "the use of a limited number of few independent variables in the logistic model might not be fully adequate to predict the M&A success" (Leepsa and Chandra, 2017).

Another potential reason for the weak predictive performance is that a logistic model

[4]Economic Value Added divided by the average net worth of the firm (Leepsa and Chandra, 2017).

may not be a good fit to predict M&A success regardless of the number of independent variables used, as it is unable to pick up on some of the complex interactions between variables. This is further developed in our thesis in section 2.4.

Further, Maloney et al. (1993) find that highly levered acquirers experienced better announcement-period returns. Their results were consistent across methodologies, where beta-adjusted abnormal returns, the numeraire portfolio approach and three-factor regression model residuals all support their findings. They explain this result by referring to Jensen (1986)'s idea that "Debt creation [...] enables managers to effectively bond their promise to pay out future cash flows". In essence, it is argued that managers of firms with high debt levels and, consequently, substantial debt servicing costs, have limited discretion to allocate cash flow as they please. Thus, less cash is spent on poor investment decisions, such as acquisitions motivated by manager self-interest, and agency costs are reduced.

Extant literature also finds significant sector-related differences in M&A success. Rozen-Bakher (2018) finds that horizontal mergers lead to integration and synergy success in the industry sector, but failure of the integration stage in the services sector. However, horizontal M&As typically hinders profitability in both sectors. Vertical M&As were a success in relation to synergy effects in the services sector, but not the industry sector. Bianconi and Tan (2019) find different instantaneous and medium-run impacts of M&As globally across the communications, technology, energy and utilities sectors from 2000-2010. Overall, some sectors tend to experience more successful acquisitions than others, which is consistent with our findings in Table 5.2.

Alhenawi and Stilwell (2017) use a logistic regression of pre-acquisition financial ratios to predict M&A success. Their study tests the hypothesis that M&A success can be explained by the acquirer's competency proxied by their pre-merger financial ratios. They measure M&A success by Tobin's Q[5], excess value and cumulative abnormal returns. The most significant financial ratios in explaining M&A success were cash ratio, debt ratio, interest coverage ratio, return on assets (ROA), return on equity (ROE) and size (Alhenawi and Stilwell, 2017). Once again, the importance of the firm's liquidity position was emphasized, alongside a focus on profitability measures. They also find that the acquirer's pre-acquisition asset turnover, earnings per share and sustainable growth

[5] Refer to Chen and Lee (1995) for a detailed explanation.

rate were positively related with success, measured by cumulative abnormal returns. In addition, they observed that cash conversion cycle and debt ratio had a negative impact on success.

Furthermore, Stein (1997) argue for the importance of internal capital markets[6] to allocate scarce resources. Unlike a bank, the executives of a firm have the ability to engage in winner-picking, which allows the firm to actively shift capital to the projects with the best return. Shin and Stulz (1998) further emphasize the importance of well-functioning internal capital markets, strengthened by high liquidity. According to Alhenawi and Stilwell (2017), these findings support the idea that having higher liquidity before an acquisition increases the likelihood of positive cumulative abnormal returns after the acquisition, which is consistent with the results of their own analysis.

Utilizing pre-acquisition financial metrics, as done by Alhenawi and Stilwell (2017) and Leepsa and Chandra (2017), is a well-established method in the field of finance research. Among other applications, this method has been shown to significantly explain credit failure (Beaver, 1966; Altman, 1968, 1984), future stock returns (Ou and Penman, 1989a,b; Lev and Thiagarajan, 1993; Piotroski, 2000) and bond ratings and yields (Ederington et al., 1987).

However, despite the emphasis on financial and strategic factors in M&A research, a meta-analysis of existing empirical research by King et al. (2004) revealed that most commonly studied variables had none or a modest effect on post-acquisition performance, as measured by cumulative abnormal returns. Some of these variables include relatedness of acquisitions, method of payment, and M&A experience. However, given the poor predictive performance and large variance, there is a need to identify more robust research methods and explanatory variables, as noted by King et al. (2004). The meta-analysis by King et al. (2004) also finds that Return of Assets (ROA), Return on Equity (ROE) and Return on Sales (ROS) are either negatively associated or insignificant for the acquiring firms in many of the studies they analyzed. Further, Romero-Martínez and García-Gómez (2017) find that structural and human integration, and integrating organizational systems, were the backbone of a successful acquisition in their in-depth study. It is clear from existing empirical research that the commonly studied variables in M&A research have

[6]The market for capital allocation within the firm.

a modest effect on post-acquisition performance, highlighting the need for new research methods and explanatory variables.

2.3.2 The organizational culture and behavioral approach

The advancing behavioural sciences have also looked at how to explain post-M&A performance, or the lack of it. Looking beyond financial measures, the cumulative trauma on employees, exacerbated by poor communication from management, have negative effects on M&A performance (Schweiger and Denisi, 1991). The leadership of the acquired firm also suffers, with increased turnover of management negatively impacting post-acquisition performance (Cannella Jr. and Hambrick, 1993; Walsh, 1988, 1989). Although there is a long-standing practice to replace executives in order to improve efficiency, realize synergies, and align culture, this research suggests that this may ultimately have a negative impact on company performance.

The relationship between culture and performance in M&A deals has yielded contradictory findings, perhaps because of the vague definitions of key variables like culture-fit and cultural compatibility (Cartwright and Schoenberg, 2006). When attempting to aggregate and generalize factors across firms, this problem is further compounded. A study by Weber (1996) found that relationships between human factors are complex and vary across industries, exacerbating the issue. In light of the difficulties of studying cultural and human factors across diverse firms, we concentrate on financial variables and sector-specific insights to provide actionable recommendations to the practitioner.

2.4 Research question development

This section contains the development of our research questions and how we intend to answer them. We seek to expand on current literature in the following ways. First, we find that extant literature mainly explores specific markets or niches. Assuming that many of the success factors may have differing effects in different areas, this makes sense. However, a manager seeking research-backed advice on acquisition success factors will find few studies relating to their specific situation. Therefore, we take a broad perspective and examine North-American stock exchange listed firms as a whole[7]. Furthermore, much of existing research bases their methodology on the logistic regression (Leepsa and Chandra, 2017; Alhenawi and Stilwell, 2017). We believe the complexity of determining acquirer success factors necessitates the use of machine learning methods[8], which can handle this complexity better, as a supplement to the logistic regression. Lastly, we interpret the results of the logistic regression and machine learning models together. This allows us to observe which results support each other across models, and which are contradictory.

2.4.1 Determining success factors

A vast body of existing literature seeks to explain the success factors of acquisitions across multiple disciplines. As discussed in the literature review, Leepsa and Chandra (2017) study success factors in the Indian manufacturing sector, while Alhenawi and Stilwell (2017) study factors of both acquirer and target. Dos Santos et al. (2008) examine international diversifying acquisitions and Harford et al. (2012) look at privately held targets. Based on the above discussion, we develop the first research question:

> **Research question 1:** Which acquirer pre-acquisition factors impact the success of an acquisition, measured by whether the acquirer achieved positive cumulative abnormal returns after the acquisition[9]?

We seek to answer the question by (1) performing logistic regression to identify statistically significant variables impacting success and (2) by examining the variable importance and partial dependence plots of the machine learning models. The machine learning models also allow us to examine the interactions between predictor variables.

2.4.2 Determining the usefulness of the results

To determine success factors, current research largely consists of financial event studies (King et al., 2004), with many studies employing logistic regression (Alhenawi and Stilwell, 2017; Leepsa and Chandra, 2017; Tsagkanos et al., 2007). One by one, statistically

[7]Further justification for this broad approach can be found in section 6. For example, Leepsa and Chandra (2017) examine the Indian manufacturing industry, but findings from this industry may not translate to other areas. In short, we believe the use of logistic regression necessitates more narrow data sets because they are unable to pick up relationships when they differ between markets or niches. The use of machine learning methods enables the use of broader data sets.

[8]We use Random Forest and Gradient Boosting Machine, see section 4.3.

[9]A mathematical representation of the success variable is shown in section 4.

significant factors are deemed important for managers to consider, with the idea being that a higher value of positively correlated variables means that your firm is positioned well for successful acquisitions, and vice versa. We intend to test whether interpreting the coefficients in this way is useful to predict which firms are likely to become successful acquirers. Therefore, we develop the second research question:

> **Research question 2:** To what extent are the predictors identified by our models practically useful for managers to predict if their firm is positioned for acquisition success?

We define a practically useful predictor as one which contributes to good predictive performance in the models, which in turn helps practitioners distinguish between successful and unsuccessful acquirers. To measure this, we make use of the ROC curve with its AUC score to evaluate the predictive performance of each model. Although the goal is not to build the best predictive model *per se*, but rather to identify success factors, poor predictive performance may indicate that a manager following the advice of the model will perform poorly when evaluating whether their firm is fit to acquire other companies. Thus, a manager should not necessarily prioritize a certain factor simply because it is statistically significant. If the variable is deemed important by a model which also exhibits good predictive performance, the likelihood that this variable should be prioritized by a manager seeking to position their firm for a successful acquisition increases. In this regard, the ROC curve and AUC score are used in combination with the other metrics to evaluate whether managers should base their decision on the results.

3 Data

3.1 Data Sample Structure

The data for this thesis is confined to acquiring companies, and the data is sourced exclusively from the COMPUSTAT, Fama-French, and Center for Research in Security Prices (CRSP) databases. The data is accessed and obtained through Wharton Research Data Services (WRDS). In the following sections we go through each data set and explain the preliminary transformations and variable creation necessary for our analysis. Section 4 contains a detailed overview of all the variables used in the analysis. The final data sample is in panel format, comprising data from each firm i in year t.

3.1.1 COMPUSTAT Database

COMPUSTAT Fundamentals (COMPUSTAT, 2023) is a widely recognized database that provides financial data for publicly traded companies in North America. The database contains a wealth of information, including income statements, balance sheets, cash flow statements, and other financial metrics that are essential for understanding a company's financial health and performance over time. Due to its value in providing insights into the financial performance of publicly traded companies, the COMPUSTAT Fundamentals database is used in this thesis.

This thesis uses the **Fundamentals Annual** data from 2010 to 2022 to obtain standard accounting figures and pre-calculated financial ratios for publicly traded companies in North America. The accounting figures are used to construct dummy variables for filtering, grouping, and data analysis, including:

Did Acquire: If a company engaged in an acquisition in a given fiscal year t, this dummy variable is set to 1 for that year. Otherwise, it is set to 0. The variable is used to create the *after acquisition* and *ever acquired* variables.

After Acquisition: If the cumulative sum of the *did acquire* variable is above or equal to 1, the *after acquisition* variable is 1. Hence, the firms in our data sample have values of 0 before they acquired a firm, and 1 after they acquired a firm. This variable is used as the before/after variable in our event study. Further, the variable is used when computing our success criteria of cumulative abnormal returns, which is calculated after an acquisition has occurred, i.e., when *after acquisition* is 1.

Ever Acquired: This dummy variable is 1 if the company has ever spent money on acquisitions. It is used for descriptive statistics where we compare companies that actively acquire to those who do not. It is also used to filter the data such that only those firms which have ever acquired are included in the data set used for the logistic and machine learning models.

Pre-calculated **financial ratios** from COMPUSTAT (2023) are used in the ratio analysis as this allows our results to be replicated to a greater degree than if we did our own calculations. We select our ratios from over 70 different financial ratios in the categories of Liquidity, Profitability, Efficiency and more. To ensure consistency with prior research, we explain the rationale for each variable used in our thesis in section 4. Like Alhenawi and Stilwell (2017), we convert the monthly ratios to yearly by computing the yearly averages of the given ratios.

3.1.2 Center for Research in Security Prices Database

The CRSP (Center for Research in Security Prices) database is an annually updated database that provides a comprehensive collection of security prices, returns, and volume data for stocks traded on these markets. The database is widely used for research on a range of topics in finance research, including mergers and acquisitions. From the CRSP database we retrieve the **Monthly Stock File** data from 2010-2022, which we convert to annual data. The stock data for each company, selected by company ticker, is used mainly in the calculation of our success criteria, cumulative abnormal returns. From this database, we gather:

Holding Period Return: The HPR is gathered and connected to our COMPUSTAT data by ticker and date. The returns are converted to yearly returns by taking the product of the monthly values (rate + 1), then subtracting 1.

S&P 500 index return: The S&P index return is the average return of the index for a given duration. It is an indicator of how well the 500 largest North American stock listed companies are doing and is therefor a proxy for market return.

Company β: The β value of an investment is a measure of the risk that investment will add to a portfolio (Perold, 2004a). Using the HPR and the S&P index return we find the beta for each company in each period. The formula used for calculating β is outlined in section 4.

3.1.3 Fama-French Database

The Fama-French database provides financial data that is frequently used in finance research. Specifically, this data set includes information on the excess return on the market and the risk-free rate, which are used to calculate expected return from the Capital Asset Pricing Model. Only the following variables [10] from this database are used in our thesis:

Market Risk Premium: The market risk premium is the difference between the expected return of the market portfolio and the risk-free rate. Given that the companies we observe are publicly traded North American companies, we use the market return of the S&P 500 as a proxy for the market portfolio return.

Risk-Free Rate: The risk-free rate used in our analysis is the one-month US Treasury bill rate.

3.1.4 Final data sample

The final data sample is created by merging the yearly COMPUSTAT, CRSP and Fama-French data outlined above by company ticker and year. Merging the datasets by company ticker[11] and date ensures correct attribution of financial ratios, returns, and beta values to their respective companies in the correct periods.

3.2 Data delimitation

In an effort to get as robust and practical results as possible, we delimit our data in the following ways. First, we choose the time-frame of 2010 to 2022 as we want the data to be as representative as possible for modern companies using M&A in the current business climate. The chosen 2010-2022 time-frame ensures that our analysis is not confounded

[10] Not to be confused with the Fama-French 3 and 5 factors.
[11] Company ticker has the following tags in the databases: COMPUSTAT (TIC) and CRSP (TICKER).

by the effects of the global financial crisis, which had sufficiently settled by the start of our study period (Bain&Company, 2023). As reported by Bain&Company (2023), global M&A deals have closely followed the overall economy since 2010, with the total global volume consistently increasing. Further, we remove extreme observations of ratios that are far beyond reasonable and affect the results to a large degree. The following changes are made to the variables:

Equity to invested capital: Negative observations are removed, as this indicates a company in dire financial distress (negative equity).

Receivable turnover: Observations above 1000 are removed, as this indicates that companies collect their accounts receivable at the extreme rate of over 1000 times per year.

Cash conversion cycle: Observations above 5000 are removed, as this indicates the companies need 5000 days or more to convert their inventory to cash flow from sales, which we consider an extreme cycle.

Current ratio: Observations above 50 are removed, as this indicates the companies have 50 dollars of current assets for every 1 dollar of current liabilities and deviates excessively from the mean.

Research and development costs to sale: Observations exceeding 1000 are removed from our study, as these are likely to represent highly niche firms, such as specialized R&D companies, that do not provide a typical representation of the broader population of firms.

Return on capital employed: Extreme observations below -10 and above 10 are removed.

Return on equity: Extreme observations below -10 and above 10 are removed.

Interest coverage ratio: Observations below -1000 and above 1000 are removed, as these indicate an extreme inability or ability to pay the companies interest expenses.

Pre-tax profit margin: Observations below -1000 are moved, again because of their extreme nature.

Debt to assets: As companies should not have a debt to assets ratio above 1, which would mean that they have more debt than assets and therefore facing bankruptcy, observations with debt to assets ratio above 1 are removed.

Approximately 2000 observations are lost from these changes. A potential problem with our time-frame selection is that companies may have been acquiring prior to 2010, which could invalidate our assumption that they start acquiring when the *did acquire* variable turns to 1. Additionally, by removing extreme and illogical observations, we may be presenting some companies in a different light than reality. E.g., if an extreme negative observation is removed, that company may now look more successful than it otherwise would. This could affect the comparison between successful and unsuccessful companies if the removed observations were skewed towards one end of the spectrum and then excluded from the final data sample.

3.3 Descriptive statistics

Our study's final sample, comprising 5796 observations identified by their ticker and date, consists of companies that have executed at least one acquisition between 2010 and 2022. Table 3.1 shows the summary statistics for all numerical independent variables used in our analysis[12].

Table 3.1 reveals that many of the financial ratios have a high standard deviation relative to the mean (high coefficient of variation), which may complicate the identification of significant relationships later in the analysis. This supports the use of machine learning techniques over linear methods like logistic regression (James et al., 2013). The high relative standard deviations indicate a high degree of variability in our data, with some companies performing significantly better or worse than others. Interestingly, Table 3.1 also suggests that the acquirers, on average, had negative Return on Capital Employed (ROCE), Return on Equity (ROE) and Return on Assets (ROA), which are widely used metrics for evaluating a company's financial performance. Table 5.1 further expands on the differences in summary statistics between successful and unsuccessful acquirers.

[12]See Table 4.1 for an overview and explanation of the variables used in this thesis.

Table 3.1: Descriptive statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
equity_invcap	5796	0.719	0.263	0.001	0.538	0.954	5.082
at_turn	5796	0.972	0.916	0.001	0.359	1.356	20.671
rect_turn	5796	19.7	53.192	0.136	5.286	11.321	913.754
profit_lct	5796	-0.041	2.186	-34.997	-0.257	0.86	44.64
cash_conversion	5796	117.019	230.699	0.014	30.446	124.489	3889.316
curr_ratio	5796	3.245	3.332	0.068	1.407	3.813	43.257
rd_sale	5796	2.564	22.362	0	0	0.126	650.486
roce	5796	-0.079	0.598	-8.818	-0.13	0.149	3.967
roe	5796	-0.21	0.912	-9.622	-0.243	0.128	7.714
debt_at	5796	0.216	0.177	0	0.061	0.332	0.921
intcov_ratio	5796	0.609	157.84	-985.92	-8.926	11.989	960.397
ptb	5796	4.315	6.293	0.13	1.221	4.559	63.858
quick_ratio	5796	2.637	3.237	0.068	0.957	2.941	43.217
roa	5796	-0.015	0.318	-2.877	-0.053	0.142	5.188
cash_ratio	5796	1.82	3.116	0	0.241	1.943	42.952
ptpm	5796	-5.052	40.71	-990	-0.204	0.1	18.903

4 Methodology

4.1 Financial measures of performance

In the field of financial research, ratio analysis is a commonly used tool with many applications, such as predicting credit failure (Altman, 1968, 1984) and future stock returns (Piotroski, 2000). In this study, we aim to introduce a selection of financial ratios motivated by a combination of extant literature and our own inquisitiveness. Table 4.1 shows the variables used in the models, as well as their description, category and research motivation. Below, we also explain each variable in detail.

Table 4.1: Variables used in the models in this thesis.

Variable	Description	Citation
Profitability		
roe	Return on equity	De Wet and Du Toit (2007)
*roa**	Return on assets	Jewell and Mankin (2011)
roce	Return on capital employed	Whiting (1986)
npm	Net profit margin	Leepsa and Chandra (2017)
*ptpm**	Pre-tax profit margin	Alhenawi and Stilwell (2017)
Liquidity		
curr_ratio	Current ratio	Anwar and Debby (2017)
*cash_ratio**	Cash ratio	Alhenawi and Stilwell (2017)
*quick_ratio**	Quick ratio	Anwar and Debby (2017)
intcov_ratio	Interest coverage ratio	Pina et al. (2017)
cash_conversion	Cash conversion cycle	Yazdanfar and Öhman (2014)
Leverage		
equity_invcap	Equity to invested capital	Alhenawi and Stilwell (2017)
debt_at	Debt to assets	Kartikasary et al. (2021)
Efficiency		
at_turn	Asset turnover	Gill et al. (2017)
rect_turn	Receivables turnover	Amanda (2019)
profit_lct	Profit to current liabilities	
Other		
ptb	Price to book	Nissim and Penman (2003)
rd_sale	R&D to sales	Shen et al. (2017)
*gsector**	Sector	Rozen-Bakher (2018)

*: Excluded from the logistic regression.

Return on assets: ROA is an indication of how profitable a company is relative to its assets, calculated by dividing net income by total assets. It is among the most important measures of a firm's performance, and indicates how effective the firm is at generating income from their assets (Jewell and Mankin, 2011). Calculated as

$$\frac{Net\ income}{Average\ total\ assets} \tag{4.1}$$

Return on equity: ROE is an indication of how profitable a company is relative to its equity, calculated by dividing net income by total equity. It measures how effectively the company uses its equity to generate net income (De Wet and Du Toit, 2007). Calculated as

$$\frac{Net\ income}{Average\ total\ equity} \tag{4.2}$$

Return on capital employed: ROCE is a financial measure which assesses the firm's ability to generate net income from the capital it has invested. A higher value indicates that a firm is more effective in leveraging its capital to generate profits. According to Whiting (1986), ROCE is regarded by most businesses as their key measure of total performance. It is calculated as

$$\frac{EBIT}{Total\ assets - Current\ liabilities} \tag{4.3}$$

Net profit margin and pre-tax profit margin: NPM and PTPM are financial ratios which measure a firm's profitability relative to its sales. The measure shows how much profit a firm can extract from its total sales (Bos et al., 2017). Leepsa and Chandra (2017) find a significant negative relationship between net profit margin and M&A success. Alhenawi and Stilwell (2017) find a significant negative relationship between operating profit margin and success.

$$npm = \frac{Net\ income}{Revenue} \qquad ptpm = \frac{Profit\ before\ taxes}{Revenue} \tag{4.4}$$

Current ratio: The current ratio is a widely-used financial metric used to assess a company's liquidity position. It is calculated by dividing current assets by current liabilities, and represents the proportion of current liabilities which can be covered by current assets. Anwar and Debby (2017) found notable differences in this ratio before and after M&A. Calculated as

$$\frac{Current\ assets}{Current\ liabilities} \tag{4.5}$$

Cash ratio: The cash ratio is a measure of a firm's ability to meet its short-term liabilities using cash and cash-equivalents. It is more conservative than the current ratio, as it only includes the most liquid assets. A high cash ratio thus indicates a strong liquidity position, while a low ratio indicates that the firm may struggle to meet its short-term liabilities. Alhenawi and Stilwell (2017) find that cash ratio is positively related with post-acquisition cumulative abnormal returns. Calculated as

$$\frac{Cash\ equivalents + Cash}{Current\ liabilities} \tag{4.6}$$

Quick ratio: Quick ratio is an indicator of a company's short term liquidity position, measuring its ability to cover short-term liabilities with current assets excluding inventory. According to Anwar and Debby (2017), quick ratio was significantly associated with post-M&A results. Therefore, the quick ratio may be an important factor for predicting acquisition success. Calculated as

$$\frac{Current\ assets - Inventory}{Current\ liabilities} \tag{4.7}$$

Interest coverage ratio: This ratio reflects the ability of an organization to meet its interest payments. A higher ratio indicates a better ability cover interest expenses. Pre-M&A interest coverage ratio is usually higher than post-M&A (Pina et al., 2017). These results indicate that an acquisition can potentially decrease a company's ability to service interest payments, underscoring the significance of a strong interest coverage ratio prior to performing an acquisition. Calculated as

$$\frac{EBIT}{Interest\ expenses} \tag{4.8}$$

Cash conversion cycle: CCC measures how many days it takes a company from spending cash on inventory to turning that inventory back into cash through sales. A lower CCC is advantageous as the firms has less cash tied up in inventory and accounts receivable. Yazdanfar and Öhman (2014) find that reducing the CCC significantly improved the profitability of a firm. Calculated as[13]

$$DIO + DSO + DPO \tag{4.9}$$

Equity to invested capital: This ratio measures the proportion of a firm's total capital coming from equity. A higher ratio implies that more of the assets are equity financed, which is often a sign of lower financial risk. Alhenawi and Stilwell (2017) find that debt ratio, the opposite of equity to invested capital, was negatively associated with the probability of acquirer success. It is calculated as

$$\frac{Common\ equity}{Invested\ capital} \tag{4.10}$$

Debt to assets: The debt to assets ratio measures the proportion of a firm's assets funded by debt. A high ratio implies that the firm is highly levered, which may indicate higher financial risk. A high debt to assets ratio typically means that the firm will struggle to raise additional capital through debt because it is already highly levered. Alhenawi and Stilwell (2017) find that debt to assets is negatively associated with acquirer success. It is calculated as

$$\frac{Total\ debt}{Total\ assets} \tag{4.11}$$

Asset turnover ratio: The ability of a company to efficiently generate net sales using its assets is measured by the asset turnover ratio. A high ratio indicates that the company

[13] Days Inventory Outstanding (DIO) is calculated as $\frac{Inventory \times Days_p}{COGS}$, Days Sales Outstanding (DSO) as $\frac{Accounts\ receivable \times Days_p}{Revenue}$ and Days Payable Outstanding (DPO) as $\frac{Accounts\ payable \times Days_p}{COGS_p}$, where $Days_p$ is the number of days in period p.

is efficient in making money through its assets, including both current and fixed assets. This ratio is a significant factor that affects the operational efficiency of production firms in particular (Gill et al., 2017). Calculated as

$$\frac{Net\ sales}{Total\ assets} \tag{4.12}$$

Receivables turnover: This ratio measures a firm's ability to collect cash from its credit sales. A higher value indicates that the firm is able to collect its outstanding receivables quickly, which is positive for the liquidity of the firm. A low ratio means that more of the firm's cash is tied up in credit for its customers. Amanda (2019) finds that higher receivables turnover is associated with a higher firm profitability.

$$\frac{Net\ credit\ sales}{Average\ accounts\ receivable} \tag{4.13}$$

Profit before depreciation to current liabilities: This financial ratio measures a firm's ability to cover its short-term obligations with operating profits before depreciation. A high profits before depreciation to current liabilities ratio implies that the firm is generating sufficient profits from its operations to cover its short-term obligations, which is positive for the firm's financial soundness.

$$\frac{Profit\ before\ depreciation}{Current\ liabilities} \tag{4.14}$$

Price to book: The P/B ratio compares the market value of a company to its book value. The book value is measured by its equity, which is equivalent to subtracting liabilities from the firm's assets. A high P/B ratio implies that the market values the firm higher than its balance sheet. This may indicate that balance sheet values are lower than the market values, or that the market expects high future profits from the firm. This ratio is among the most widely studied in financial literature (Pae et al., 2005; Nissim and Penman, 2003).

$$\frac{Market\ value}{Book\ value} \tag{4.15}$$

Research and development to sales: This ratio measures how much a firm is spending on research and development relative to its sales. A high ratio indicates that the firm spends a large proportion of its income on R&D. On the other hand, high R&D spending could imply that there is less capital available for acquisitions. Karna et al. (2022) find that the long-term effects on R&D on profitability are greater than the short-term effects and that higher R&D expenditure reduces short-term profitability.

$$\frac{R\&D\ expenses}{Sales} \tag{4.16}$$

Sector: We use the global industry classification standard (GICS) to classify firms into their respective sectors. A study by Rozen-Bakher (2018) finds that M&A success varied significantly between sectors, echoed by our results in Table 5.2. Doytch and Cakan (2011) find that M&A activity was positively associated with economic growth in the services sector, but not in other sectors.

4.2 Measuring acquirer success

This section shows the development of our binary success variable by starting with the variable definition and subsequently working through its constituents. We measure acquisition success by an indicator variable Z_i for each company i which is 1 if the final cumulative abnormal return (CAR) after the acquisition is positive, and 0 otherwise (equation 4.17).

$$Z_i = \begin{cases} 1 & \text{if } CAR_{i,after\_acquisition=1} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{4.17}$$

An alternative would be to compare CAR before and after the acquisition, deeming the acquisition successful if they achieved a higher CAR after the acquisition than before. However, if a firm had its acquisition take place early in the data sample, they would have a relatively shorter period to generate CAR before the acquisition, and a relatively long period to generate CAR after the acquisition[14]. Such firms would then be deemed

[14]See Figure 5.1 for an example where two firms have unequal periods before/after they become acquirers.

successful more often by nature of how we measure success. A work-around for this could be to limit the data included to an equal length before and after the acquisition, with the trade-off that much of the data is lost. In line with Leepsa and Chandra (2017) and Alhenawi and Stilwell (2017), we therefore deem the acquisition successful if they produce positive (greater than 0) CAR following the acquisition. The consequence of this is that we deem some acquirers successful even when they were already successful before the acquisition took place. However, this must mean that they managed to maintain positive CAR even when they acquired another firm. Thus, even if the acquisition itself was not necessarily the reason for the positive CAR, they still managed to outperform the market following the acquisition. Therefore, positive CAR after the acquisition is chosen as the success criteria for our thesis, as well as for Leepsa and Chandra (2017) and Alhenawi and Stilwell (2017).

There are several reasons for using cumulative abnormal returns as the basis for measuring firm performance and thus, acquisition success. First, measuring success by stock returns alone would ignore the opportunity cost of equity (Sharpe, 1964). E.g., if a firm produces a return of 4% and another firm 8%, the investor is missing out on 4% of return. Furthermore, standard financial theory dictates that the price of risk must also be accounted for (Sharpe, 1964; Perold, 2004b; Rossi, 2016; Ross, 1978). We therefore use CAPM to calculate abnormal returns, which are the excess returns after the cost of risk is accounted for. CAR therefore accounts for both the opportunity cost of equity and its riskiness.

The cumulative abnormal return of an acquiring company i is computed by taking the sum of its abnormal returns for all periods $t \in T$ after the acquisition took place, as in equation 4.18. The abnormal return return of company i at time t is calculated by taking its return and subtracting its expected return according to CAPM, shown in 4.19.

$$CAR_i = \sum_{t \in T} AR_{i,t} \tag{4.18}$$

$$AR_{i,t} = r_{i,t} - \mathbb{E}(r_{i,t}) \tag{4.19}$$

The Capital Asset Pricing Model (Equation 4.20) is still one of the most important methods for evaluating the cost of capital and performance of firms (Fama and French, 2004). It states that the expected return of a firm is given by the risk-free rate and a market premium multiplied by the firm's beta value. The model posits that a company's β, which captures its degree of risk, determines its expected returns.

$$\mathbb{E}(r_{i,t}) = r_{f,t} + (\mathbb{E}(r_{m,t}) - r_{f,t})\beta_i \tag{4.20}$$

The β value of firm i is calculated as shown in equation 4.21, where r_i is the return of firm i, r_f is the risk-free rate and r_m is the market return in the same period (Campbell and Mei, 1993). All values are calculated for each period t. The β of firm i is the slope of the ordinary least-squares linear regression between r_i and r_m. We calculate the β based on all available observations prior to the acquisition.

$$\beta_i = \frac{\mathrm{Cov}(r_i, r_m)}{\mathrm{Var}(r_m)} \tag{4.21}$$

4.3 The models

In this thesis, we employ three distinct models: a logistic regression, as well as two supervised machine learning techniques – random forest and gradient boosting. Logistic regression was selected for this study due to its widespread utilization in prior research and its ability to assess the significance of the variables. The machine learning models are selected for their ability to model complex non-linear relationships and high predictive power (Ryll and Seidens, 2019) and is a departure from studies such as Leepsa and Chandra (2017) and Alhenawi and Stilwell (2017). Random forest and gradient boosting are both tree-based techniques, which make them particularly well suited for structured data (James et al., 2013), which this thesis builds on.

4.3.1 Logistic regression

This thesis calls for a binary logistic regression, in which there are two possible outcomes: the acquisition is either a success or a failure. We estimate the probability of success given the explanatory variables (Equation 4.22). Thus, for each firm's independent variables $X_1, ..., X_p$, the model estimates the probability that the acquisition was successful.

$$P(Success = 1 \mid X_1, ..., X_p) \tag{4.22}$$

The logistic model predicts the probability of a successful acquisition $p(X)$ with p predictors according to equation 4.23 (James et al., 2013).

$$p(X) = P(Success = 1 \mid X_1, ..., X_p) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + ... + \beta_p X_p)}} \tag{4.23}$$

This equation can be rewritten to be linear in X as shown in equation 4.24. The left hand side of this equation is called the logit.

$$\log\left(\frac{p(X)}{1 - p(X)}\right) = \beta_0 + \beta_1 X_1 + ... + \beta_p X_p \tag{4.24}$$

For this thesis, the logistic regression equation is

$$\begin{aligned} \log\left(\frac{p(X)}{1 - p(X)}\right) =& \beta_0 + \beta_1 \text{equity\_invcap} + \beta_2 \text{at\_turn} + \beta_3 \text{rect\_turn} + \\ & \beta_4 \text{profit\_lct} + \beta_5 \text{cash\_conversion} + \beta_6 \text{curr\_ratio} + \\ & \beta_7 \text{rd\_sale} + \beta_8 \text{npm} + \beta_9 \text{roce} + \beta_{10} \text{roe} + \beta_{11} \text{debt\_at} + \\ & \beta_{12} \text{intcov\_ratio} + \beta_{13} \text{ptb} + \beta_{14} \text{rect\_turn} + \epsilon \end{aligned} \tag{4.25}$$

where β_0 is the intercept, $\beta_1, \ldots, \beta_{14}$ are the coefficients of the corresponding variables, and ϵ is the error term.

4.3.2 Random forest

Random Forest is a supervised machine learning technique which works by creating an ensemble of decision trees. In this thesis, we apply the technique to a classification problem. While regular decision trees are simpler to interpret and understand, they typically have weak predictive performance (James et al., 2013). This is mainly because decision trees suffer from high variance, meaning that the trees (and therefore the predictions) are substantially different with only a small change in the data. To estimate a classification tree, the classification error rate is used. The point is to assign an observation to the class in which it most frequently occurs. In this context, the classification error rate is the fraction of observations put in a region that do not belong to the most common class (James et al., 2013):

$$E = 1 - \max_{k} (\hat{p}_{m,k}) \tag{4.26}$$

Here, $\hat{p}_{m,k}$ is the proportion of observations in the mth region that are from the kth class.

To overcome the problem of variance with decision trees, we can aggregate the trees, a technique called bagging. Take a set of independent observations $Z_1, ..., Z_n$, each with a variance σ^2. The variance of the mean $\bar{Z}$ is then σ^2/n. This means that if we draw many training sets from the population and estimate a tree model from each, and then take the average, the variance is inversely proportional to n. We only have one training set, but we can repeatedly sample this set by bootstrapping to obtain B training sets. These can then be averaged to get a lower-variance model:

$$\hat{f}_{\text{avg}}(x) = \frac{1}{B} \sum_{b \in B} \hat{f}_b(x) \tag{4.27}$$

The problem with bagging is that if there are relatively strong predictors present in the data (which in itself is what we are trying to identify), they will almost always be used in the top split (James et al., 2013). This means that many of the trees will be similar and therefore not notably improve the predictive performance (Altman and Krzywinski, 2017). To get around this problem, we can randomly select a subset of variables which the model is allowed to use each time a tree is grown. This ensures that more of the variables have a chance to be included at a higher level in the tree (Altman and Krzywinski, 2017). A benefit of the random forest model is that it will not overfit with increasing B, so we can B sufficiently high to where the error rate stabilizes. In accordance with James et al. (2013), we set $m = \sqrt{p}$, where m is the number of variables selected for each tree and p is the total number of explanatory variables. For our thesis, we set $m = 4$ and the number of trees to $n = 3000$. We use the `randomForest` package in `R` to fit the RF model.

4.3.3 Gradient Boosting Machine (GBM)

Contrary to bagging and random forests, gradient boosted trees are not built independent of each other. Instead, boosted trees are grown sequentially, i.e., they are grown based on the information from the previous trees. Boosted trees are grown based on the residuals from the previous tree, instead of the outcome variable. This process is repeated for B iterations. By fitting new trees to the residuals, the model is slowly improved in the areas where it does not perform well (James et al., 2013). Gradient boosted decision trees are used in a wide variety of financial applications (Gogas and Papadimitriou, 2021), such as credit risk (Chang et al., 2018), customer loyalty (Machado et al., 2019), predicting bank failure (Climent et al., 2019) and financial distress (Liu et al., 2019). We set the number of trees to $n = 3000$ and the interaction depth to $d = 4$. Both of these values are set based on trial and error in accordance with James et al. (2013). 3000 trees were sufficiently high for the error rate to stabilize, and an interaction depth of 4 yielded the best results in our data. We use the `gbm` package in `R` to fit the GBM model.

4.4 Validation and interpretation methods

4.4.1 Receiver Operating Characteristic (ROC) curve

The challenge with classification based on the above models is that the outputted probabilities must be transformed back into a binary variable. This is achieved by setting a threshold value for the probability, such that any probability greater than the threshold results in predicting *Success*. A low threshold means that we classify more of the actual success cases as a *Success*, but at the cost of also classifying more failure cases as a *Success*. I.e., there is a trade-off between increasing the true positive rate at the cost of a higher false positive rate. The problem is illustrated in Table 4.2.

Table 4.2: Confusion matrix

		Predicted value	
		Success	Not Success
Real value	Success	True positive	False negative
	Not Success	False positive	True negative

The ROC graph is used to visualize the trade-off between increasing the true positive rate at the cost of increasing the false positive rate (Fawcett, 2006). The x-axis of the ROC graph shows the false positive rate (FPR), while the y-axis shows the true positive rate (TPR) (Equation 4.28). When the threshold is incrementally reduces from a value of 1, the rate of true positives increase, but at the expense of a higher rate of false positives. For a good prediction model, we want a sharp rise in TPR with a low increase in the FPR (James et al., 2013).

$$TPR = \frac{TP}{TP + FN} \qquad\qquad FPR = \frac{FP}{FP + TN} \tag{4.28}$$

By graphing TPR against FPR and calculating the area under the curve (AUC), we get a sense of the prediction performance of the model. An AUC closer to 1 means an excellent predictive performance, while an AUC score closer to 0.5 means that the predictions are as poor as a random classifier (Fawcett, 2006). The AUC of a classifier is equivalent to the probability that the classifier will rank a randomly chosen positive instance higher than a randomly chosen negative instance (Fawcett, 2006). In this thesis, we use AUC as the primary method of scoring the predictive performance of the models used. We use the `pROC` and `ROCR` packages in `R` (Robin et al., 2011) to draw ROC curves and calculate the AUC.

4.4.2 Variable Importance Plot

The Variable Importance Plot displays the average node purity of each predictor in the model (Gregorutti et al., 2017). Since a random forest model consists of multiple trees bagged together, we cannot directly interpret the effects of each predictor. However, we can obtain a summary of the overall importance of each predictor in the classification model using the Gini index. Specifically, we can measure how much the Gini index (4.29) is decreased by each split (predictor) in each tree, which is then averaged over all B trees.

$$G = \sum_{k \in K} \hat{p}_{m,k}(1 - \hat{p}_{m,k}) \tag{4.29}$$

Here, $\hat{p}_{m,k}$ is the proportion of training observations in the mth region from the kth class.

From equation 4.29, it is apparent that when the value of $\hat{p}_{m,k}$ is close to zero or one, the Gini index will be smaller. The Gini index is also referred to as *node purity* because a low value indicates that a node predominantly contains observations from a single class (James et al., 2013). It follows that if a split decreases the Gini index by a large amount, then the predictor at that split must be good at separating the data into the correct regions. Hence, a high node purity value indicates that the variable was important in predicting acquisition success.

4.4.3 Partial Dependence Plot

Unfortunately, the results of complex nonparametric models – like random forests and gradient boosting machines – are challenging to understand because the models themselves are black boxes (Goldstein et al., 2015). Contrary to traditional statistical techniques, there are no coefficients to tell us the relationship between variables. This problem has limited the adoption of machine learning in M&A research. While determining the importance of predictors in the model is crucial, it say nothing of the *relationship* between the dependent variable and the predictors. Fortunately, recent developments in the field of machine learning have led to the introduction of partial dependence plots, which offer a new solution to the challenge of examining the relationship between a subset of the features and the response variable (Greenwell, 2017). These plots work by visualizing the relationship between the factors and the response while accounting for the average effect of the other predictors in the model. For the classification problem in this thesis with two responses $k = \{1, 2\}$, we calculate the partial dependence function[15] as

$$f_k(x) = \log(p_k(x)) - \frac{1}{2}\sum_{k=1}^{2}\log(p_k(x)) \tag{4.30}$$

where $p_k(x)$ is the predicted probability of class k. Here, the two classes are success ($Z = 1$) and failure ($Z = 0$). We then plot $f_k(x)$ against x. We use the `pdp` package in R to create the partial dependence plots.

[15]See Greenwell (2017) for a complete mathematical overview of partial dependence plots.

4.4.4 Cross-validation

The machine learning models used in this thesis can adapt to almost any data set and model complex relationships, which means that there is a high chance that they pick up patterns in the data which (1) do not make sense from a finance perspective and (2) are not reproducible (Kuhn et al., 2013). I.e., there is a high chance of overfitting[16] the models, the result being that the usability of the models on new data would be worsened. For this thesis in particular, it would mean that the models do not perform well in predicting acquisition success for hold-out data and real-life applications. To rectify this problem, we split the data into a training set (70% of observations) and a test set (30% of observations). All models are trained on the training set, while predictions and validation is performed on the test set. This ensures that if the models are overfitted to the training data and thus perform poorly on new data, we pick up on it when evaluating the model with the test set. Furthermore, this thesis uses panel data[17]. The time-series component of panel data means that if we included a time variable in the data, it could pick up on year effects which would make the model worse when predicting acquisition success for firms outside the years included when training the model. The model would thus be less useful for predictions before or after the years included in our data. We therefore exclude time as a variable in all models.

4.4.5 Statistical significance of ROC curves and their AUC

To measure the statistical significance of the difference between the ROC curves and AUCs, this thesis utilizes (1) the bootstrapping method, (2) DeLong's method and (3) Venkatraman's method. These methods are too long fully account for here, so we settle for a brief description of how they work and refer the interested reader to the respective references for details. The methods compare two models at a time. The bootstrapping method is based on non-parametric re-sampling and the percentile method (Carpenter and Bithell, 2000)[18]. This method re-samples the data n times and calculates AUC scores based on these values. Then, we check if the mean AUC values for the two models are significantly different by calculating the z-statistic as

[16] Refer to (Berrar, 2018) for a comprehensive definition of overfitting.

[17] A time-series of cross-sectional data.

[18] See sections 2.1 and 3.3 in Carpenter and Bithell (2000) for non-parametric re-sampling and the percentile method, respectively.

$$z = \frac{\overline{AUC_1} - \overline{AUC_2}}{s} \tag{4.31}$$

DeLong's method is performed as described in DeLong et al. (1988) using the algorithm of Sun and Xu (2014). This method also checks if the calculated AUC values are significantly different by calculating the z-statistic as

$$z = \frac{\hat{\theta}^{(1)} - \hat{\theta}^{(2)}}{\sqrt{\mathbb{V}[\hat{\theta}^{(1)} - \hat{\theta}^{(2)}]}} = \frac{\hat{\theta}^{(1)} - \hat{\theta}^{(2)}}{\sqrt{\mathbb{V}[\hat{\theta}^{(1)}] + \mathbb{V}[\hat{\theta}^{(2)}] - 2\mathbb{C}[\hat{\theta}^{(1)}, \hat{\theta}^{(2)}]}} \tag{4.32}$$

where $\hat{\theta}^{(i)}$ is the estimated AUC of the ith ROC curve. The z-statistics of the bootstrapping method and DeLong's method follow the standard normal distribution $\mathcal{N}(0, 1)$. We therefore compare this value to a range of critical values from the standard normal distribution, such as 1.96 at the 5% significance level. For bootsrapping and DeLong's, we have H_0: The true difference in AUC is 0.

Venkatraman's method (Venkatraman and Begg, 1996) checks whether the true difference in at least one ROC operating point is non-zero, with H_0: The true difference in every ROC operating point is 0. This method is distribution-free. The test statistic is calculated as

$$E = \sum_{k=1}^{n-1} |e_{.k}| \tag{4.33}$$

where $e_{.k}$ is the difference in the total number of errors of each test when the kth classification point is used. The reference distribution, to which the test statistic E is compared, is obtained by randomly permuting the pairs and recomputing the statistic as explained in Venkatraman and Begg (1996). The two-sided p-value from comparing E to the reference distribution is then used to determine the significance of the test.

We used $n = 500$ permutations for all three methods and the `roc.test` function from the `pROC` package in `R` to carry out the tests.

5 Analysis

5.1 Data exploration

This section contains preliminary data exploration. Table 5.1 presents descriptive statistics by whether the acquirer was successful after acquisition, along with an F-test of the difference between the group means. Most group means are significantly different from each other, implying that successful acquirers have different pre-acquisition conditions than the failures. Notably, we find that asset turnover is significantly higher in successful acquirers. Successful acquirers have a significantly shorter cash conversion cycle than unsuccessful acquirers, and failures had a significantly higher price to book ratio. Equity to invested capital, receivables turnover and debt to assets were the only non-significant between-group differences at a 5% significance level.

Table 5.1: Descriptive statistics by success

Success?	No			Yes			
Variable	N	Mean	SD	N	Mean	SD	Test
equity_invcap	5063	0.719	0.263	733	0.717	0.262	F= 0.043
at_turn	5063	0.933	0.798	733	1.246	1.464	F= 76.13***
rect_turn	5063	19.749	53.86	733	19.361	48.354	F= 0.034
profit_lct	5063	-0.109	2.281	733	0.433	1.262	F= 39.59***
cash_conversion	5063	121.277	244.287	733	87.609	87.571	F= 13.667***
curr_ratio	5063	3.315	3.456	733	2.757	2.244	F= 18.006***
rd_sale	5063	2.916	23.902	733	0.134	1.055	F= 9.922***
roce	5063	-0.096	0.614	733	0.034	0.45	F= 30.499***
roe	5063	-0.237	0.955	733	-0.024	0.477	F= 35.296***
debt_at	5063	0.217	0.178	733	0.204	0.171	F= 3.615*
intcov_ratio	5063	-1.507	160.059	733	15.222	140.797	F= 7.2***
ptb	5063	4.475	6.507	733	3.207	4.389	F= 26.145***
quick_ratio	5063	2.715	3.369	733	2.094	2.039	F= 23.66***
roa	5063	-0.026	0.331	733	0.066	0.19	F= 54.55***
cash_ratio	5063	1.909	3.25	733	1.208	1.851	F= 32.555***
ptpm	5063	-5.761	43.507	733	-0.157	1.852	F= 12.154***

Statistical significance markers: * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table 5.2 presents the distribution of firms between the sectors for unsuccessful and successful acquirers in the data. We perform a χ^2 test to determine if there is a significant association between the categorical variables *success* and *gsector*. The null hypothesis is that there is no significant association between the variables. We find that the variables are significantly associated ($p < 0.01$), implying that the distribution of successful acquirers across the sectors was different from the distribution of unsuccessful acquirers. We find that a greater proportion of successful acquirers operate in industrials and information technology compared to unsuccessful acquirers. On the other hand, health care firms are disproportionately unsuccessful acquirers in this data set. None of the successful acquirers in our data operate in the real estate sector.

Table 5.2: Acquisition success by sector. Includes a χ^2 test for the association between gsector and success.

Success?	No		Yes		
Variable	N	Percent	N	Percent	Test
gsector	5057		733		$\chi^2 = 133.504^{***}$
... energy	352	7%	34	4.6%	
... materials	270	5.3%	63	8.6%	
... industrials	658	13%	154	21%	
... consumer_discretionary	904	17.9%	109	14.9%	
... consumer_staples	336	6.6%	46	6.3%	
... health_care	1288	25.5%	91	12.4%	
... financials	90	1.8%	20	2.7%	
... information_technology	636	12.6%	145	19.8%	
... communication_services	125	2.5%	15	2%	
... utilities	336	6.6%	56	7.6%	
... real_estate	62	1.2%	0	0%	

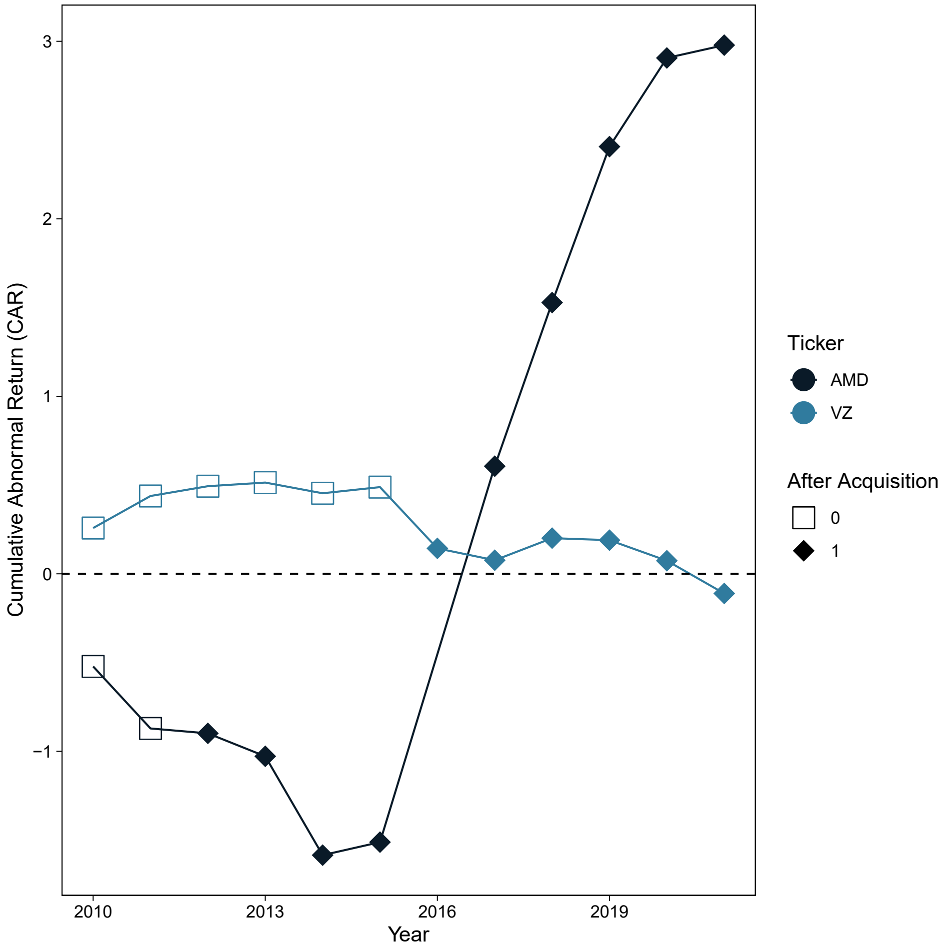
Statistical significance markers: * p<0.1; ** p<0.05; *** p<0.01

An informal analysis of the Cumulative Abnormal Return (CAR) of AMD and Verizon before and after acquisition is depicted in Figure 5.1. Prior to becoming acquirers, Verizon exhibited a positive CAR. However, following the acquisition, their CAR declined[19] and ultimately reached a negative value, indicating an unsuccessful acquirer in our analysis. Conversely, AMD exhibited a negative CAR prior to the acquisition, but experienced a notable positive CAR in the subsequent years[20].

[19]Note that the calculation of CAR before and after acquisition is performed independently. I.e., the CAR after acquisition does not continue from the CAR before acquisition, but rather starts from 0. Thus, the first CAR value after acquisition corresponds to the abnormal return for that particular year.

[20]It is important to note that this does not imply a causal relationship, but rather serves as an illustrative example of the data sample used in our analysis.

Figure 5.1: Cumulative Abnormal Return before and after acquisition for Advanced Micro Devices (AMD) and Verizon (VZ).



5.2 Logistic Model

The logistic model is run on panel data, containing information on each firm i in year t. While financial ratios are commonly used as independent variables in financial analysis, a major challenge is the high degree of multicollinearity induced by their similarity. We used the variance inflation factor (VIF) to measure whether a variable was problematic in this regard. Consistent with Alhenawi and Stilwell (2017), variables with $VIF > 10$ were removed. The models before and after trimming the high-VIF variables quick ratio, ROA, cash ratio and pre-tax profit margin are shown in Table 5.3. The following analysis is based on Model 2, which is the trimmed model.

As seen in Table 5.3, we find a significant, positive effect on the odds of a successful acquisition for asset turnover. Furthermore, we find a significant negative effect on the

Table 5.3: Logistic models

	Model 1		Model 2	
	Coef.	Std. error	Coef.	Std. error
(Intercept)	-0.0394	(0.3987)	-0.0363	(0.3934)
equity_invcap	-1.7834	$(0.3874)^{***}$	-1.7374	$(0.3828)^{***}$
at_turn	0.1634	$(0.0615)^{**}$	0.2058	$(0.0574)^{***}$
rect_turn	-0.0003	(0.0010)	-0.0005	(0.0010)
profit_lct	-0.0271	(0.0491)	0.0079	(0.0434)
cash_conversion	-0.0008	(0.0005)	-0.0004	(0.0004)
curr_ratio	0.0661	(0.0613)	-0.0175	(0.0215)
rd_sale	0.0594	(0.1066)	0.0329	(0.1071)
npm	0.2713	(0.1422)	0.1266	(0.0691)
roce	0.0641	(0.1455)	0.0759	(0.1433)
roe	0.0451	(0.1045)	0.0513	(0.0985)
debt_at	-2.8544	$(0.5784)^{***}$	-2.7921	$(0.5728)^{***}$
intcov_ratio	-0.0003	(0.0004)	-0.0003	(0.0004)
ptb	-0.0364	$(0.0122)^{**}$	-0.0417	$(0.0123)^{***}$
quick_ratio	0.0461	(0.1017)		
roa	0.1093	(0.3485)		
cash_ratio	-0.1667	(0.0927)		
ptpm	-0.1325	(0.1280)		
AIC	2921.0357		2919.6012	
BIC	3034.5878		3007.9195	
Log Likelihood	-1442.5179		-1445.8006	
Deviance	2885.0357		2891.6012	
Num. obs.	4058		4058	

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

odds of a successful acquisition for equity to invested capital, debt to assets and the price to book ratio. Our findings for asset turnover are consistent with Leepsa and Chandra (2017). However, contrary to their findings, we see no significant relationship between pre-acquisition net profit margin and acquisition success. Current ratio, receivables turnover, profit to current liabilities, cash conversion cycle, R&D to sales, net profit margin, return on capital employed, return on equity and interest coverage ratio had no significant impact on the probability of successful acquisition in our data.

These findings indicate that *ceteris paribus*, acquiring firms with high pre-acquisition asset turnover ratios are better suited to generate positive cumulative abnormal returns following the acquisition of other firms. While Sunjoko and Arilyn (2016) find that asset turnover did not affect the profitability of a firm and Alhenawi and Stilwell (2017) find no correlation between asset turnover and M&A success, we and Leepsa and Chandra (2017) find a significant, positive correlation. The discrepancy may be caused by different methods of measuring acquisition success or differces in the data studied.

Contrary to Alhenawi and Stilwell (2017), Leepsa and Chandra (2017) and Amanda (2019), our findings indicate that there was no significant relationship between current ratio and being a successful acquirer. Typically, a high current ratio signifies a healthy liquidity situation. These results are strange in the context that liquid firms are often found to have more successful acquisitions because their internal capital markets are stronger (Stein, 1997; Shin and Stulz, 1998; Alhenawi and Stilwell, 2017).

Firms with a high debt to assets ratio were less likely to be successful acquirers compared to those with lower debt to assets. Acquisitions are often financed through borrowing money. One popular financing strategy for acquisitions is the leveraged buyout (LBO) (Taylor, 1988). However, to finance the buyout through increased leverage, the pre-acquisition leverage cannot be too high. This is further supported by the internal market argument above, because high leverage requires higher debt servicing, thus reducing available liquidity in the internal market. It may be that the negative correlation is due to already highly leveraged firms struggling to find financing for their acquisitions at a fair price, thus hampering their profitability post-acquisition.

Lastly, we find that firms with a higher price to book ratio were less likely to achieve successful acquisitions. Alhenawi and Stilwell (2017) find no significant relationship between price to book, and consequently remove it in their reduced model. A high price to book ratio indicates either that (1) the market value of the company's assets is overvalued, or (2) the book value of the company's assets are undervalued. This finding aligns with Jensen (2005)'s argument that overvalued equity can lead to the erosion of a firm's core values due to agency costs[21]. Specifically, organizational pressures on managers to engage in increasingly risky investments in order to maintain the valuation can contribute to this erosion of shareholder value.

Although a discussion of the factors impacting acquisition success can be interesting in its own right, this thesis aims to illuminate how such knowledge can be used as a tool[22] for

[21] Refer to the section 2 for more comprehensive explanation of agency costs

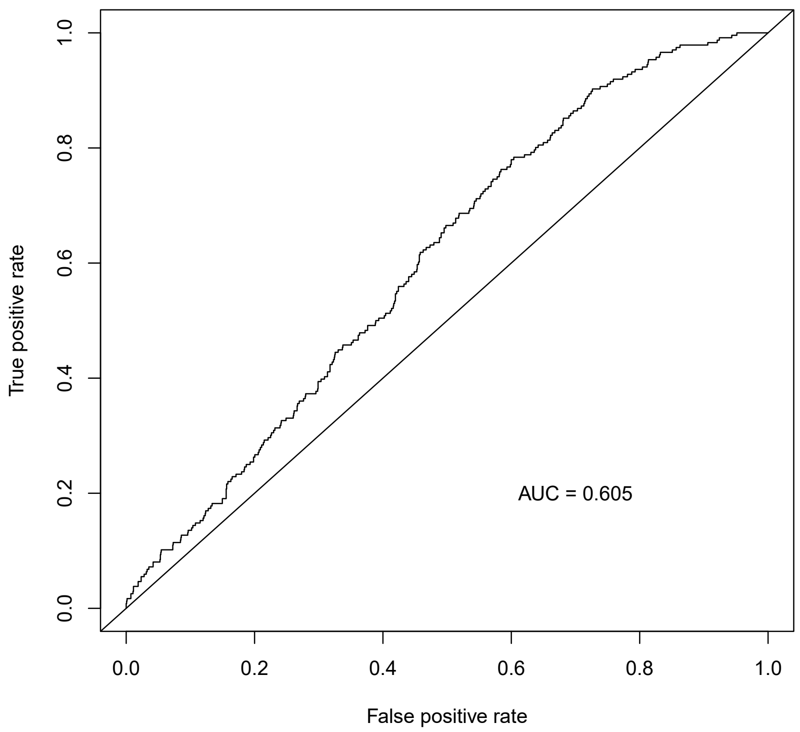
[22] As discussed in section 2.4, we wish to identify factors which can be used to make accurate real-world predictions about which firms have the necessary pre-acquisition conditions to become successful acquirers.

managers considering an acquisition. Existing literature mostly examines the *marginal* effect of each factor. Managers can then compare their own firm against which factors correlate with acquirer success. Taking our logistic regression results at face value, we could recommend that managers of firms with high asset turnover go ahead with an acquisition as they have a higher probability of success than others. Likewise, we could recommend managers of firms with a high equity to invested capital, debt to assets and price to book ratio to shy away from acquisition activity. Would following these guidelines enable managers to distinguish the successful acquirers from the failures? To assess this, we let the logistic model predict the probability of success for the acquisition cases in the test set. Yet, for the practitioner, it is not enough to calculate a probability of success. The manager must decide whether to go ahead with the acquisition or not. To achieve this, we set a threshold value for the probability, above which the company is marked as a successful acquirer. Acquirers with probabilities below the threshold are marked as unsuccessful.

Setting the threshold value entails a trade-off between increasing the true positive rate at the cost of increasing the false positive rate. Leepsa and Chandra (2017) report that their model correctly predicted 69.2% of cases. However, this says nothing of the model's ability to discriminate between successes and failures. For example, if 69.2% of the acquisitions in their data were successes, a model guessing *success* each time would perform as well as their model, even though such a model would be useless in practice. A more sophisticated measure of the predictive performance of the model is to use the ROC curve with its accompanying AUC score (Shams et al., 2011). This allows us to assess the trade-off between TPR and FPR, where a model which gains a large increase in TPR at the expense of a low increase in FPR performs well. This is equivalent to assessing the model based on its AUC score, where a higher score indicates better predictive performance.

From the ROC curve in Figure 5.2, it is apparent that the predictive performance of the logistic model is poor. It has practically no ability to discriminate between successes and failures, as an increase in TPR comes at the cost of an almost equally large increase in FPR. Although the logistic model identified multiple statistically significant predictors of acquisition success, it fails to convert those results into useful predictions. The marginal interpretations of the logistic model are therefore of little use to the manager contemplating

Figure 5.2: ROC curve for the logistic model

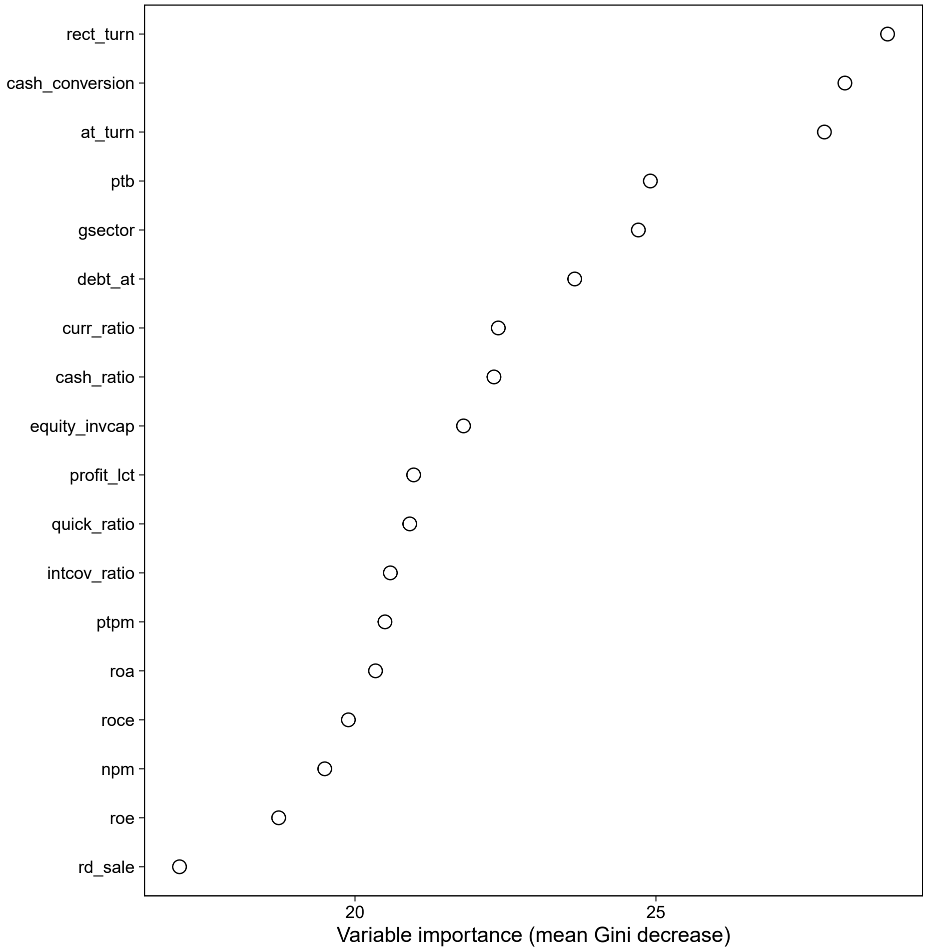


whether their firm is fit for acquisitions. The logistic model simply does not capture the complex relationships between the variables well enough to be a useful tool for predicting acquisition success. Hence, we turn to machine learning.

5.3 Random Forest Model

While we expect the random forest model to have better predictive performance, we lose the marginal interpretation of each predictor. I.e., we can no longer say that a variable alone significantly increases or decreases the probability of acquirer success. Instead, the variable importance and partial dependence plots (Greenwell, 2017) allow us to explore which variables are most important in explaining acquisition success, and interpret the relationship between the predictors and the probability of success (Strobl et al., 2008). As discussed, the logistic regression model suffered from multicollinearity at the inclusion of highly correlated predictors. It also fails to pick up complex interactions between predictors. Both these problems are resolved by using a random forest model (Strobl et al., 2008), which also allows for the inclusion of more predictors[23].

Figure 5.3: Variable Importance Plot for the Random Forest model

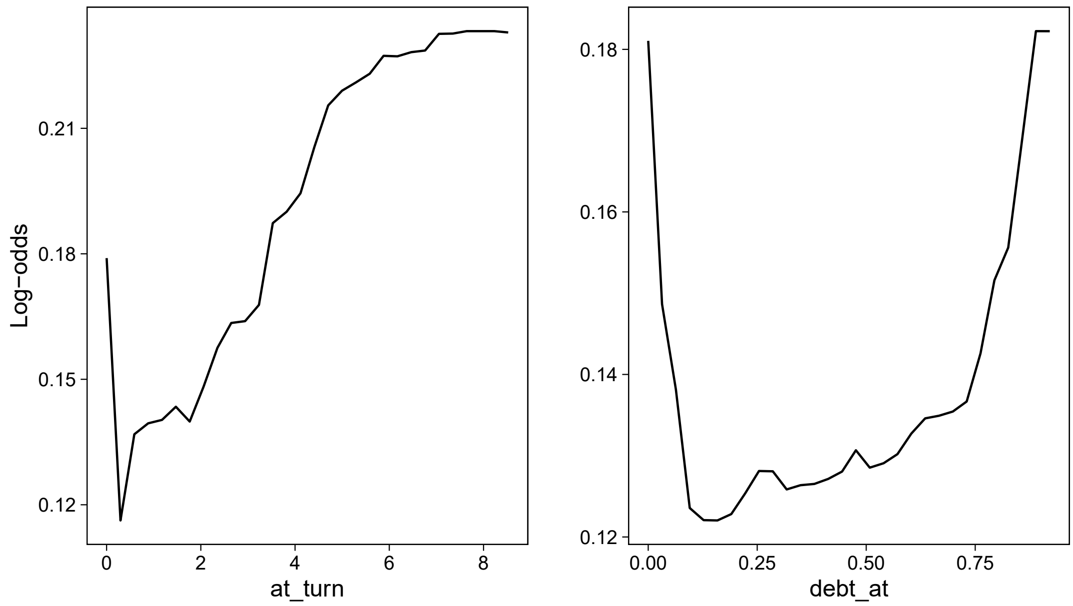


From Figure 5.3, it is apparent that receivables turnover, cash conversion cycle, asset turnover and price to book were the most important predictors. The least important variables were return on capital employed, net profit margin, return on equity and R&D to sales. Although ROE, ROA and NPM are among the most widely used measures firm performance (Heikal et al., 2014), they were among the least important in predicting acquirer success. Therefore, basing acquisition decisions on traditional measures of firm performance may not be sufficient to ensure successful acquisitions. Interestingly, the difference in node purity between the most and least important variables is relatively low, indicating that none of the variables used are much more important than others. Also, the similar node purity values indicate that many of the variables *together* predict success, instead of a few variables alone. This further supports our previous findings that

[23]Refer back to Table 4.1 for an overview of which variables are included in the logistic regression and which are added in the machine learning models.

interpreting the marginal effect of the variables in a logistic regression in isolation is of little use when predicting whether an acquisition is a success. The predictors interact to create complex relationships, making the random forest model a good fit.

Figure 5.4: Partial dependence plots for debt to assets and asset turnover based on the random forest model, plotted independently while accounting for the average effect of the other predictors in the model.

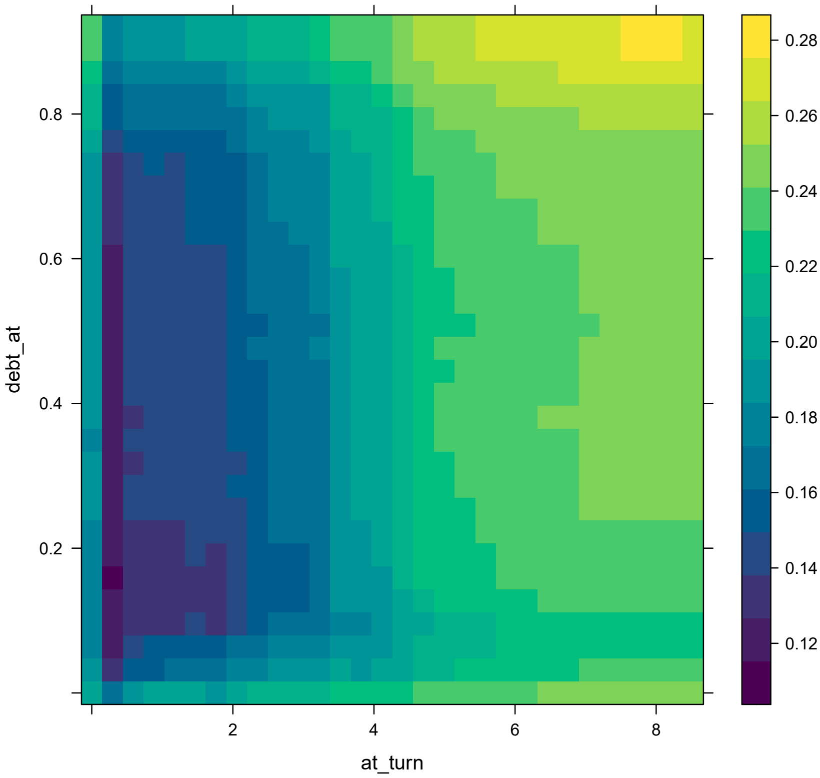


Partial dependence plots for all variables can be found in Figure A2.1 in the appendix. In an effort to keep the analysis concise, we choose to closely examine asset turnover and debt to assets ratios as they are among the most crucial measures for evaluating a firm's performance (Gill et al., 2017) and leverage. In addition, research has established that leverage has a notable impact on acquisition success (Maloney et al., 1993; Jensen, 1986). Partial dependence plots for asset turnover and debt to assets are drawn in Figure 5.4. These show the relationship between the log-odds of success and each predictor, while including the average effect of the other predictors in the model. While the plots fail to include the full interactions in the model (Greenwell, 2017), they show that higher asset turnover is generally associated with a greater probability of acquirer success. Also, extreme values[24] of debt to assets were associated with a higher probability of success. This is in opposition to the internal market argument (Stein, 1997; Shin and Stulz, 1998; Alhenawi and Stilwell, 2017), where we would expect lower probabilities of success for higher ratios of debt to assets. However, in line with our findings, Maloney et al. (1993)

[24] Values closer to 0 and 1, indicating that the firm was either not leveraged at all, or had extremely high leverage.

find that acquirer returns[25] are greater the higher the leverage of the acquirer, arguing that higher debt reduces the leeway managers have to endeavour in poor acquisitions. Hence, high leverage reduces the occurrence of acquisitions motivated by the abundance of capital.

Figure 5.5: Partial dependence plot for debt to assets and asset turnover based on the random forest model. Color scale represents the logit, with a higher value corresponding to a greater probability of success.

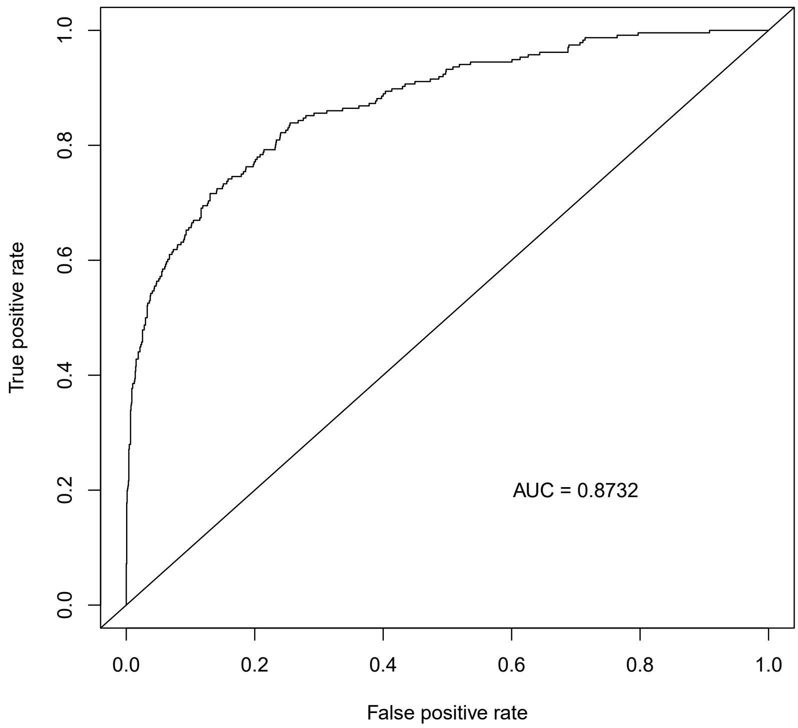


The partial dependence plot for asset turnover and debt to assets together is drawn in Figure 5.5. This plot picks up the the *joint* effect of the two predictors on the probability of success. The interaction between debt to assets and asset turnover are thus included in the model, while factoring in the average effect of the other predictors. We see that firms with low leverage and a poor asset turnover ratios are less likely to become successful acquirers compared to highly leveraged, high asset turnover firms. The exception is firms with extremely low debt to assets, indicating low leverage. This finding supports the argument that higher debt keeps managers from initiating acquisitions based on their own self-interest (Gaughan, 2003; Seth et al., 2000), effectively hampering empire-building

[25]Measured by beta-adjusted abnormal returns.

practices. Since the plot does not include all predictors, these results must be interpreted with caution.

Figure 5.6: ROC curve for the random forest model. Measuring true positive rate (TPR) vs false positive rate (FPR).



The ROC curve is shown in Figure 5.6. Contrary to the logistic model, the random forest model achieves great increases in TPR at the expense of modest increases in FPR. This results in an excellent AUC score of 0.8732. The random forest is able to discriminate between the success and failure cases, and can therefore to a far greater degree predict which firms are fit to become successful acquirers and which are likely to fail. The inclusion of complex relationships facilitate better predictive accuracy compared to the logistic model, indicating the insufficiency of logistic regression for managers contemplating an acquisition. Based on the higher AUC score, acquisition decisions informed by the random forest model are expected to result in better real-world results.

5.4 Gradient boosting machine

In addition to the random forest, we trained a gradient boosting machine to predict acquirer success. It has the same limitations as a random forest in that the marginal effect of each variable cannot be predicted directly. Instead, variable importance plots and partial dependence plots are used. The variable importance plot is shown in Figure 5.7. The most important predictors were acquirer sector, receivables turnover, cash conversion cycle and asset turnover. The least important variables were the net profit margin, pre-tax profit margin, quick ratio and return on equity. Unlike the random forest model, which presented a relatively uniform pattern of variable importance values, the gradient boosting machine displayed substantial variability in the variable importance values. This indicates that the gradient boosting machine found a few variables which contributed most of the predictive power, while it also identified some which had practically no impact on acquirer success. Acquirer sector was by far the most important predictor, supporting the notion that acquirer success varies across sectors (Rozen-Bakher, 2018).

Figure 5.7: Variable importance for the gradient boosting machine.

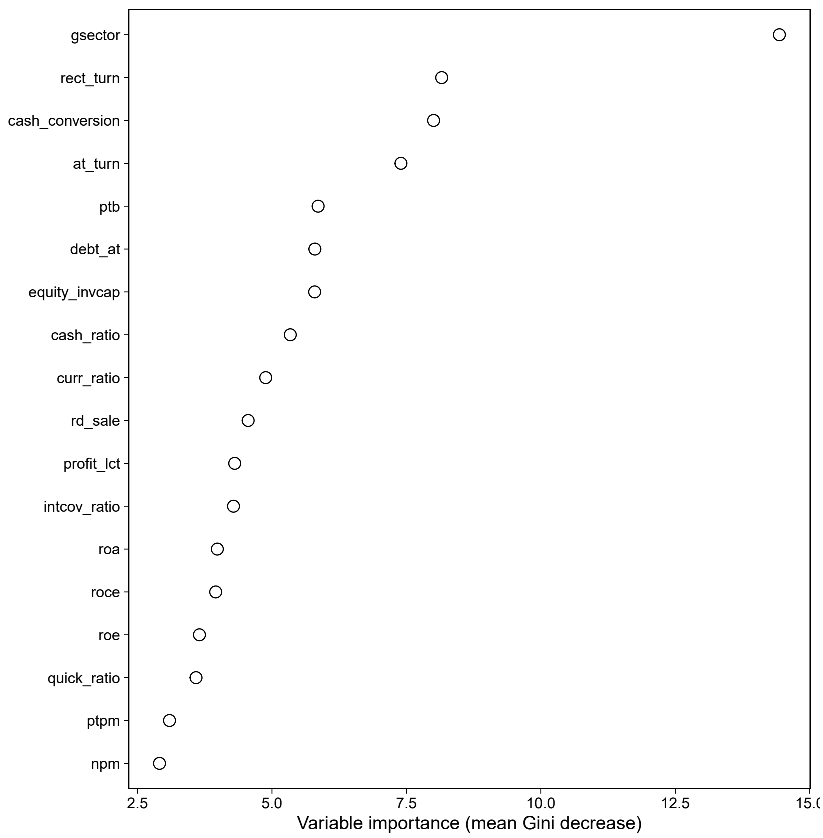


Figure 5.8: Partial dependence plots for debt to assets and asset turnover based on the gradient boosting machine model, plotted independently while accounting for the average effect of the other predictors in the model.

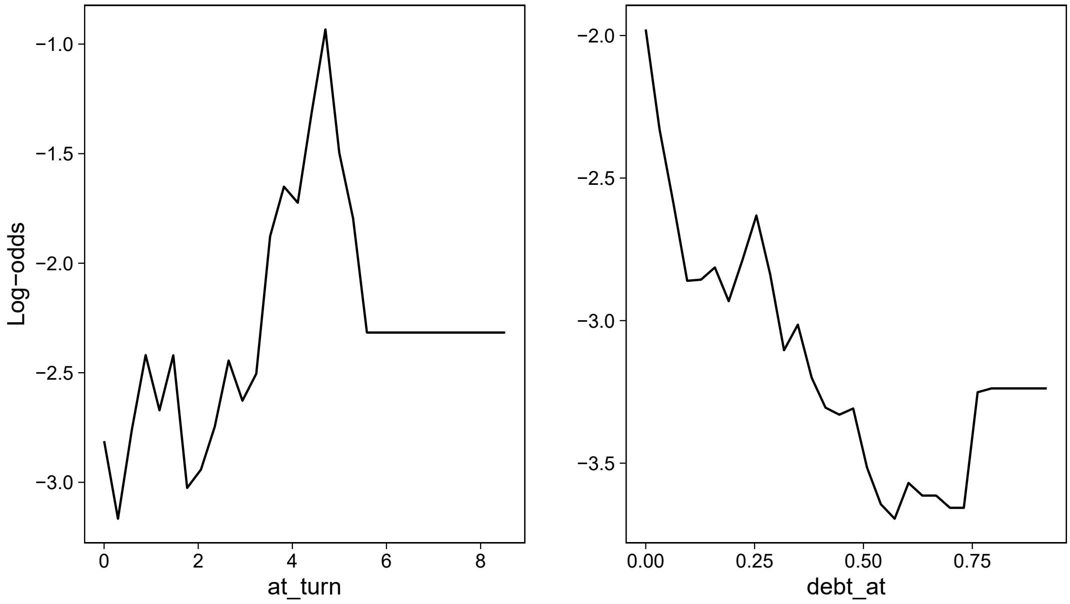
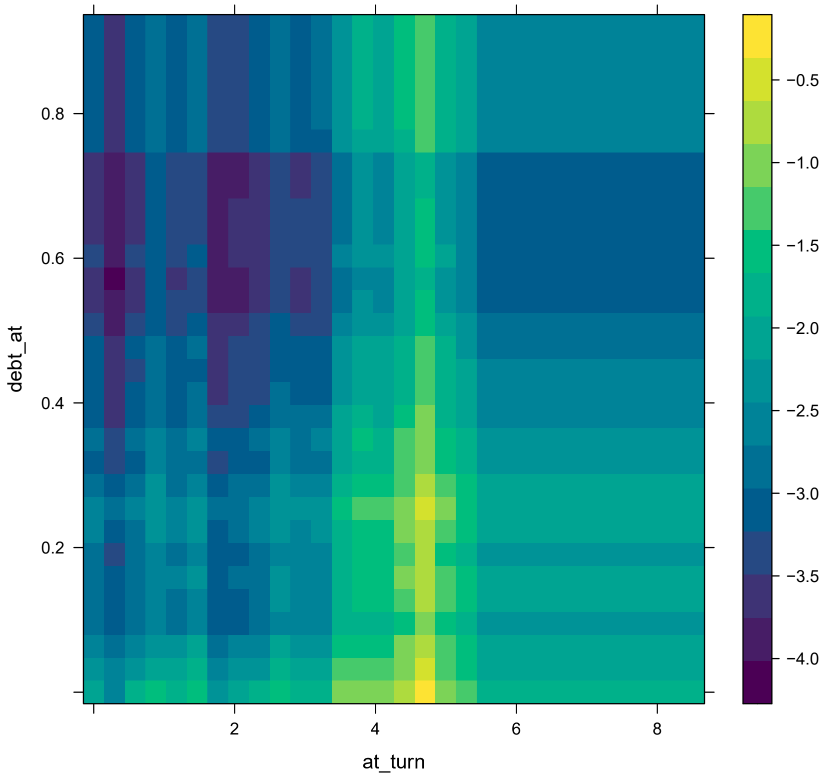


Figure 5.8 shows the partial dependence plots for asset turnover and debt to assets. Our findings suggest that asset turnover was overall positively associated with the probability of success. Debt to assets is negatively associated with the probability of success, except for highly levered firms. Again, we observe higher predicted probabilities of acquirer success at the extreme values of debt to assets. The increased probability of success for highly levered firms, which we also found in the random forest model, supports the agency theory problem that higher debt reduces managers leeway to perform acquisitions motivated by their self-interest. The relationship between the log-odds and the variables are certainly non-linear, further supporting the use of more complex models than the logistic regression.

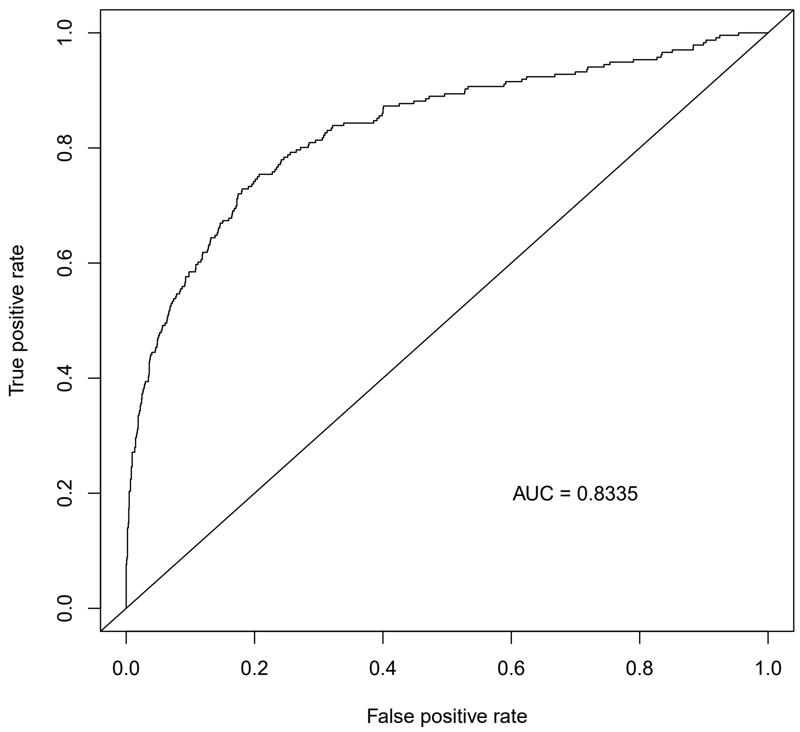
The joint partial dependence plot for debt to assets and asset turnover is shown in Figure 5.9. Consistent with the single-predictor plots in Figure 5.8, higher asset turnover was associated with a higher probability of success, while a high debt to assets ratio was associated with a lower probability of success, except for extremely levered firms. From Figure 5.9, it is also apparent that a high probability of success from a high debt to assets ratio was not the case when the asset turnover was low. Firms with a low asset turnover and high debt to assets were the least successful acquirers. The remaining partial dependence plots for the gradient boosting machine are drawn in Figure A2.2 in the appendix. There, equity to invested capital and the quick ratio appear negatively associated with being a successful acquirer, while the current ratio and return on capital employed appear positively associated with acquirer success.

Figure 5.9: Partial dependence for debt to assets and asset turnover based on the gradient boosting machine. Color scale represents the logit (log of the model's predicted probability), with a higher value corresponding to a greater probability of success.



The predictive performance of the gradient boosting machine is measured with the ROC curve and AUC score in Figure 5.10. The AUC score of the gradient boosting machine is 0.8335. Hence, it outperforms the logistic model, gaining large increases in TPR at the expense of low increases in FPR, yet falls slightly behind the random forest model for our dataset.

Figure 5.10: ROC curve for the gradient boosting machine.



5.5 Comparison of the models

In this section, we present a brief comparison of the results from the three models. The implications of the comparison are discussed in section 6. First, we take a closer look at the four significant variables of the logistic regression (Table 5.3), comparing the relationships to the partial dependence plots (Figures 5.4, 5.8, A2.1 and A2.2) of the machine learning models. The comparison is summarized in Table 5.4.

The partial dependence plots indicate that acquirer success rates are higher for firms with debt to assets ratios near 0 or 1, while the lowest probabilities are observed for firms with ratios in between. On the other hand, the logistic model suggests an overall negative correlation, perhaps due to this being the most prevalent correlation in the data and its inability to pick up on a non-linear relationship with the current model setup. Hence, it appears that the partial dependence plots and logistic regression coefficients are generally consistent for the majority of debt to asset ratios, with the exception of heavily leveraged firms that demonstrate a greater likelihood of success based on the partial dependence plots.

The equity to invested capital ratio is significant and negatively associated with acquirer success in the logistic regression. The partial dependence plots of the random forest and gradient boosting machine also indicate a negative association. Hence, the results of all three models suggest a negative relationship between equity to invested capital and acquirer success.

Asset turnover is significant and positively related to acquirer success in the logistic regression. The partial dependence plots of both machine learning models support a positive association. Hence, all models point to a positive relationship between the acquirer's asset turnover and acquisition success.

The price to book ratio exhibits conflicting results across the models. This variable is significant and negatively associated with acquirer success in the logistic regression, yet has a more complicated relationship in the partial dependence plots. The partial dependence plot of the random forest model shows a sharp negative association for low values of price to book, after which follows a positive relationship. This implies that the logistic regression model may be influenced by the sharp negative relationship observed at lower levels of price to book, while the impact of higher price to book values may be weakened by a relatively smaller number of observations. The partial dependence plot from the gradient boosting machine also exhibits the negative relationship for low values of price to book, after which the effect flattens out. Overall, the logistic regression and gradient boosting machine point to a negative relationship.

Table 5.4: The significant variables of the logistic regression and their association with success across models.

Variable	Logistic	RF	GBM
equity_invcap	−	−	−
at_turn	+	+	+
debt_at	−	0	−
ptb	−	0	−

+/−: Positively/negatively associated.

0: Non-linearly associated.

In current M&A literature, such as in Leepsa and Chandra (2017) and Alhenawi and Stilwell (2017), a model is typically deemed successful if it identifies variables which are statistically significant in explaining acquirer success. However, we demonstrate that although the logistic model identified several significant variables, the model as a whole was practically useless in discriminating between successes and failures. Table 5.5 shows the models' predictive performance as measured by AUC. The random forest and gradient boosting machine far outperform the logistic model in their predictive capability. Our goal is primarily to identify which factors managers should focus on when contemplating an acquisition to maximize their chances of success. In this regard, high predictive performance of the model is not a goal in itself. However, we believe predictive performance can in this case be used as a proxy for how well a manager will perform if they follow the advice of the models. It may not be interesting to a manager to know that certain factors are positively or negatively correlated with acquisition success, if using this information does not result in better predictions about whether their firm is fit for acquisitions.

Table 5.5: AUC scores.

	AUC
Logistic	0.6050
Random forest	0.8732
Grandient Boosting Machine	0.8335

Overall, many of the most important variables in the machine learning models were also significant in the logistic regression; however, this was not the case for all variables. Notably, one of the most important predictors for the random forest and gradient boosting machine was cash conversion cycle, yet this factor was insignificant in the logistic model. This suggests that the relationship was either non-linear in the logit or includes interactions with the other variables not picked up on by the logistic model. Asset turnover was significantly, positively correlated with acquisition success in the logistic model, and the partial dependence plots from the random forest and gradient boosting machine also suggest a positive relationship. The variable importance plots of both machine learning models also suggest that this was an important factor. Thus, all three models suggest that higher pre-acquisition asset turnover firms were more successful acquirers.

Receivables turnover was among the most important predictors in both the random forest and gradient boosting machine, yet insignificant in the logistic regression. Equity to invested capital was far from the most important variables, yet significant in the logistic regression. Evidently, importance and significance are fundamentally different.

6 Discussion

6.1 Validation and robustness

In this thesis, we compare the predictive powers of the three models by their respective ROC curves and AUC scores. In Table 5.5, the AUC scores of the machine learning models were far higher than that of the logistic model, with the random forest model having a slightly higher AUC than the gradient boosting machine. To measure whether the observed differences in AUC scores and ROC curves are not merely random, we use use three validation methods shown in Table 6.1 to examine the statistical significance of the differences. First, bootstrapping is used to measure whether the observed AUC scores are significantly different. Our results indicate a statistically significant difference when comparing the AUC scores obtained from the random forest and gradient boosting machine models, the random forest and logistic models, and the gradient boosting machine and logistic models. The differences between the machine learning models and the logistic model are particularly significant (p-values $< 2.2^{-16}$), owing to the larger differences in AUC scores between these models. The DeLong method gives the same results, where the AUC scores for all models are significantly different from each other. The results from the Venkatraman method imply that the difference in at least one ROC operating point is non-zero.

Table 6.1: Significance tests for the ROC curves. Bootstrap and Venkatraman are calculated with $n = 500$ permutations. All results are from paired tests.

	Bootstrap		DeLong		Venkatraman	
	D	p-value	Z	p-value	E	p-value
RF vs GBM	3.920	8.9e-05	3.7122	2.1e-04	2.8e04	2.2e-16
RF vs Logistic	13.64	2.2e-16	13.535	2.2e-16	1.9e05	2.2e-16
GBM vs Logistic	10.52	2.2e-16	10.343	2.2e-16	1.6e05	2.2e-16

As shown in section 4.3.1, the logit should be linear in its predictors. We check whether this is the case for each predictor in Figure A1.1 in the appendix. There, we find that many of the predictors are non-linear in the logit, implying that a transformation of the variable could have made it significant in the logistic regression. With enough work, this could be a viable option. However, as discussed by Cartwright and Schoenberg (2006), the prescriptions from the academic research are not reaching practitioners. Complex variable transformations may make it even harder for prescriptions to reach practitioners, as results become harder to explain in a simple manner. Therefore, we again argue for the use of models which inherently take care of complex data without the need for transformations, such as the random forest and gradient boosting machine.

In the logistic regression, outliers can have a significant impact on the coefficients and predictions of the model, especially if they are influential points. However, random forest and gradient boosting machine models are less sensitive to outliers than logistic regression because they are based on decision trees that partition the data into smaller subgroups (James et al., 2013). These models use an ensemble approach, where multiple decision trees are combined to generate predictions. Therefore, outliers may not have a significant impact on our machine learning models. Nevertheless, we still pre-processed the data by removing outliers as explained in section 3 before training the machine learning models to ensure this would not be a problem. The resulting standard residuals from the logistic regression are shown in Figure A1.2 in the appendix. All but one observation is within three standard residuals. The acquirer failure cases had notably low standard residuals. A plot of Cook's distance[26] values is provided in the appendix as Figure A1.3, which indicates that only three observations were particularly influential.

6.2 Implications of the analysis

In this section, we first address the practical implications of our analysis before moving on to discuss its more general implications. King et al. (2004) advise managers to be as explicit as possible about how, why and where acquisitions can be reasonably expected to strengthen their firm, and that vague rationalizations that go no farther than the typical synergy argument should be viewed with skepticism. We therefore present explicit advice here.

[26]Cook's distance measures the influence of a data point in a regression analysis. It is used to identify influential data points that may require further investigation (Cook, 1977).

6.2.1 Practical implications

The results from our analysis using all three models indicate a negative association between higher equity to invested capital and acquirer success. In light of this, our recommendation to managers is to exercise caution when considering an acquisition for firms with low debt. Furthermore, our analysis across all models consistently demonstrated a positive relationship between asset turnover and acquirer success. Therefore, managers may advocate for the pursuit of acquisitions if their firm has high asset turnover. The logistic regression and gradient boosting machine models both demonstrated a negative association between debt to assets and price to book ratio. In contrast, the random forest model revealed a more complex relationship. Thus, unlike equity to invested capital and asset turnover, we cannot provide unequivocal advice.

Even in the cases where all models indicate the same correlation between success and a predictor, we have contended that the relationships can be more intricate due to the complex interplay between the predictors in the models. The complexity of the task precludes us from offering simple advice that can be universally applied by managers. Therefore, we propose that the optimal approach for managers contemplating an acquisition is to directly use the machine learning models to calculate their own probability of acquirer success. This would give managers further information to support their decision, and they can use the information as an independent measure of whether they should acquire, instead of the usual synergy argument. In recent years, the increasing power of computers and the availability of machine learning tools as packages in programming languages such as `R` and `Python` have made it easier to adopt machine learning. This has made it more feasible for managers to use the machine learning techniques we propose here or request a similar analysis from consultants.

However, managers may face challenges in convincing the board and other stakeholders to make acquisition decisions based solely on the probability output of a machine learning model, particularly if the managers themselves lack a comprehensive understanding of the model. We believe this to be one of the most important hurdles preventing the use of machine learning for such applications. However, partial dependence plots are now available, providing insight into the workings of the machine learning models. This gives managers a tool to understand the workings of machine learning models better themselves, and to explain the results to stakeholders. We therefore believe that the direct use of machine learning by managers considering an acquisition is an important avenue to explore in the years to come.

6.2.2 General implications

The following discussion explores the more general implications of our analysis. When companies are faced with the decision to perform acquisitions, managers need research-backed advice. Our results indicate that the relationship between well-researched financial ratio variables are too complex for a reductionist approach, where the practitioner is supposed to base their decisions on the findings one variable at a time. In M&A literature, there exists a multitude of lists with criteria to be considered, as well as research articles arguing for a few critical financial ratios, but managers might find this advice inadequately actionable. As discussed in section 2, the growing literature on M&As has not resulted in increased success for stakeholders (Cartwright and Schoenberg, 2006; King et al., 2004), supporting this notion. Whether this is rooted in the practitioner's inability to act on the advice, or the advice itself being difficult to put into practice, the fact remains: too many M&As fail from a shareholder perspective (Cartwright and Schoenberg, 2006; King et al., 2004).

From our analysis of the machine learning models used, their predictive power is unmatched by the more traditional logistic regression. Thus, we argue that there is a need for more sophisticated decision support systems for managers seeking to undertake acquisitions which create shareholder value. Based on the AUC score of the random forest model and gradient boosting machines, they not only outperforms the logistic model, but are also able to predict acquirer success more accurately than the M&A success rate we see in practice (King et al., 2004), adding to its merit. These findings also further support Cartwright and Schoenberg (2006)'s third explanation of the the failings of current M&As – that there is a need for new methods to explain M&A success.

An important distinction in the field of M&A research is whether we are examining which firms *should* acquire other firms or *how* an acquirer can be successful once they have decided to acquire another firm. Our thesis focuses on the former because advances in how to perform a successful acquisition have not translated into meaningful increases in success rates (Cartwright and Schoenberg, 2006; King et al., 2004). To improve acquirer success rates, our study suggests that it may be more effective to focus on who is fit to acquire, rather than improving the execution of the acquisition process itself. This involves avoiding acquisitions by companies that are not well-suited for them, while identifying and pursuing acquisitions for companies with favorable pre-acquisition conditions. We therefore argue that acquisitions should be used more sparingly. While there are good reasons for managers to initiate acquisitions[27], managerial empire-building unrestrained by the board of directors continues to be a prevalent motivation for acquisition activity (Trautwein, 1990; Gaughan, 2003). We believe that boards and shareholders would be better fit to check such practices if they focused more on whether their firm should be acquiring others at all, and had the tools to evaluate it. In accordance with research question 1, together with the growing body of research on the matter, we therefore attempt to take a step towards uncovering which firms should be acquiring others at all, and which factors these firms possess that others do not.

As per King et al. (2004), the antecedents to successful M&A activity are not yet found conclusively. However, as Cartwright and Schoenberg (2006) argue, this may be caused by an inability of the models often used (Alhenawi and Stilwell, 2017; Leepsa and Chandra, 2017) to capture the true relationship between variables. Our partial dependence plots seek to uncover some of these relationships. We find that some relationships are not merely non-linear, but also highly dependent on other variables. I.e., the effect of one variable on acquirer success is influenced by other variables, not too dissimilar to how an interaction term in the logistic model behaves. This supports our argument that these relationships are too complex for a one-variable-at-a-time approach when determining whether a company is fit for acquisition activity, offering a potential explanation for why practitioners are finding it hard to adopt the prescriptions of researchers in the field.

It is worth noting that certain variables may exhibit significant effects in one study but be regarded as insignificant in another study, thereby highlighting the variability in the identification of statistically significant factors across different research endeavors. This is likely a result of the studies looking at different markets, countries and sectors. To exemplify, there could be a positive relationship between acquirer success and debt to assets in the manufacturing sector, but a negative relationship between the same variables

[27] See section 2.1.2 for a review on the literature on this matter.

in utilities companies. At an even more granular level, one firm could exhibit a positive relationship, while another a negative relationship. Looking at both sectors at the same time might not reveal any significant relationship when performing logistic regression because the coefficient estimates would be closer to zero as the positives and negatives cancel each other out, and the standard error is higher. These examples show why identifying advice which can be applied across firms and sectors is so difficult. Luckily, capturing such complex non-linear relationships is exactly the strength of the supervised machine learning models we use (Ryll and Seidens, 2019). Therefore, we argue that the use of machine learning enables the use of broader sets of data, which again makes the results applicable to a wider range of practitioners. This is particularly relevant to research question 2, as we seek to investigate the practical usefulness of the results in predicting a firm's potential to be a successful acquirer.

The results from both machine learning models imply that highly levered firms had a greater probability of success than those with lower leverage. This is consistent with Maloney et al. (1993) and Jensen (1986), who argued that "debt creation [...] enables managers to effectively bond their promise to pay out future cash flows". On the other hand, our results also indicate that higher leverage can negatively impact acquirer success as it reduces the liquidity of the firm's internal capital market. In addition, debt can come with its own problems as it increases financial risk. We therefore argue that firms with excess cash and managers eager to acquire others should increase their leverage enough to restrain them from performing poor acquisitions, but not so high that the added financial risk becomes problematic.

6.3 Challenges and limitations

In this subsection, we discuss some of the challenges and limitations of the thesis, including the complexity of the relationships between variables, conflicting results across models, the availability of data for unlisted companies, the impact of outliers, multicollinearity issues in logistic regression, and the limitations of the Capital Asset Pricing Model.

6.3.1 Comparing effects and conflicting results

In this thesis, we often compare the effects of variables across the models. Certainly, this is not necessarily appropriate as the ML models include additional predictors over the logistic regression, and the two machine learning models work in completely different ways. However, from the perspective of the practitioner seeking advice on whether their firm has the necessary pre-acquisition conditions to become a successful acquirer, conflicting results across models may indicate that the relationship is either not well-enough understood for them to make decisions based on or too complex for one of the models.

The implications of conflicting results across models for practitioners can be significant, especially when it comes to decision-making. This can make it difficult for practitioners to confidently make decisions based on the available data. For example, if one model suggests that a certain variable is important for success, while another model suggests that it is not, practitioners may be unsure which result to trust. According to King et al. (2004), no variable was deemed significant by more than three independent studies. We find it unlikely that practitioners are able to stay updated on the vast amount of research on the field, especially when the research itself does not conclusively point in one direction. Even those who make the attempt are likely to encounter studies which prescribe the exact opposite solutions from one another. With regards to this, it is no wonder that M&A success rates continue to stay low (King et al., 2004; Cartwright and Schoenberg, 2006).

6.3.2 Data availability

In our thesis, we aimed to use only widely accessible variables. This means that any practitioner can calculate the financial ratios we used for their own firm. However, when it comes to calculating abnormal returns, the availability of stock return information may be a limiting factor, as it's primarily available for listed companies. For unlisted companies, a comparable result could be obtained by substituting cumulative abnormal returns with EVA as the basis for the success variable. To estimate the firm's β, the cost of equity can be determined using comparable companies and the CAPM approach.

6.3.3 Ratio similarities and multicollinearity

An argument for using the machine learning models instead of the logistic regression with financial ratios is that many ratios are often similar to each other, leading to multicollinearity issues in the model. In turn, this can lead to inflated standard errors of the coefficient estimates. However, this restriction is not present in the machine learning models used, such as random forest and gradient boosting machine models, since they are not affected by multicollinearity (James et al., 2013). This means that more predictors can be used in these models, which we expect to translate to better predictive performance and insights into the relationships between financial ratios and acquirer success.

6.3.4 CAPM assumptions and limitations

As explained, the Capital Asset Pricing Model is widely used to estimate the expected return of a firm based on its risk. However, CAPM has several assumptions and limitations that can adversely affect the accuracy of its predictions. Key assumptions of the model[28] include the existence of a risk-free asset and the efficient market hypothesis. As a result, any dependent variable built on the CAPM framework, such as the acquirer success variable in this thesis, inherits these same assumptions and limitations.

6.3.5 Partial dependence plot computational cost

When drawing partial dependence plots with two variables, a compromise must be made between the resolution of the plot and the computational cost of generating it. Specifically, the PDPs with two variables in our study were drawn at a resolution of just 30 by 30. Drawing PDPs at higher resolutions would provide a more detailed diagram of the relationship between the variables, but the computations necessary to do so increase with n^2. Unfortunately, the computational expense of drawing high-resolution PDPs limited our ability to explore more finely grained relationships between variables. Nonetheless, the PDPs we used still provided valuable insights into the relationships between variables in our machine learning models.

[28] See Michaud (2013) for a comprehensive outline of CAPM.

7 Conclusion

Regarding the first research question[29], our findings indicate that higher pre-acquisition asset turnover is associated with post-acquisition success. On the other hand, lower pre-acquisition equity to invested capital, debt to assets and price to book were associated with post-acquisition acquirer success. The variable importance plots from the random forest and gradient boosting machine both indicate that cash conversion cycle was the most important variable, even though it was insignificant in the logistic regression. Sector also played a major role in explaining acquirer success according to the machine learning models. We also find that the machine learning models far outperform the logistic model in predicting which acquirers are positioned for acquisition success, and had AUC scores which were significantly superior to the logistic model. In addition, our results indicate that, in line with Jensen (1986)'s agency theory, higher debt reduces the occurrence of unsuccessful acquisition activity as managers have less leeway to spend excess capital on empire building.

Regarding the second research question[30], we find that many of the variables identified in the logistic regression, while statistically significant, are not interesting for managers and other practitioners seeking to position their firm for successful acquisitions due to poor predictive performance. In particular, the predictive performance of the logistic model is inadequate, measured by its ROC curve's AUC. Our findings point to a possible explanation of the prevalent failures of acquisitions: the models on which the advice is based often exhibit poor predictive performance. Thus, practitioners following the advice cannot expect good performance either. We believe that this discrepancy has been largely overlooked in much of the literature and therefore prescribe the direct use of machine learning by managers to discover their own acquisition readiness.

Consistent with King et al. (2004), we believe that being selective in whether you should acquire others at all is more important than how to successfully integrate two firms once an acquisition is already imminent. We are hopeful that future research on the matter will help shed light on possible solutions, as we have attempted here.

[29] Which acquirer pre-acquisition factors impact the success of an acquisition?

[30] To what extent are the predictors identified by our models practically useful for managers to predict if their firm is positioned for acquisition success?

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Appendix

A1 Logistic regression diagnostics

Figure A1.1: Scatter plots showing each predictor vs the logit. A loess curve with uncertainty bands is drawn for each plot.

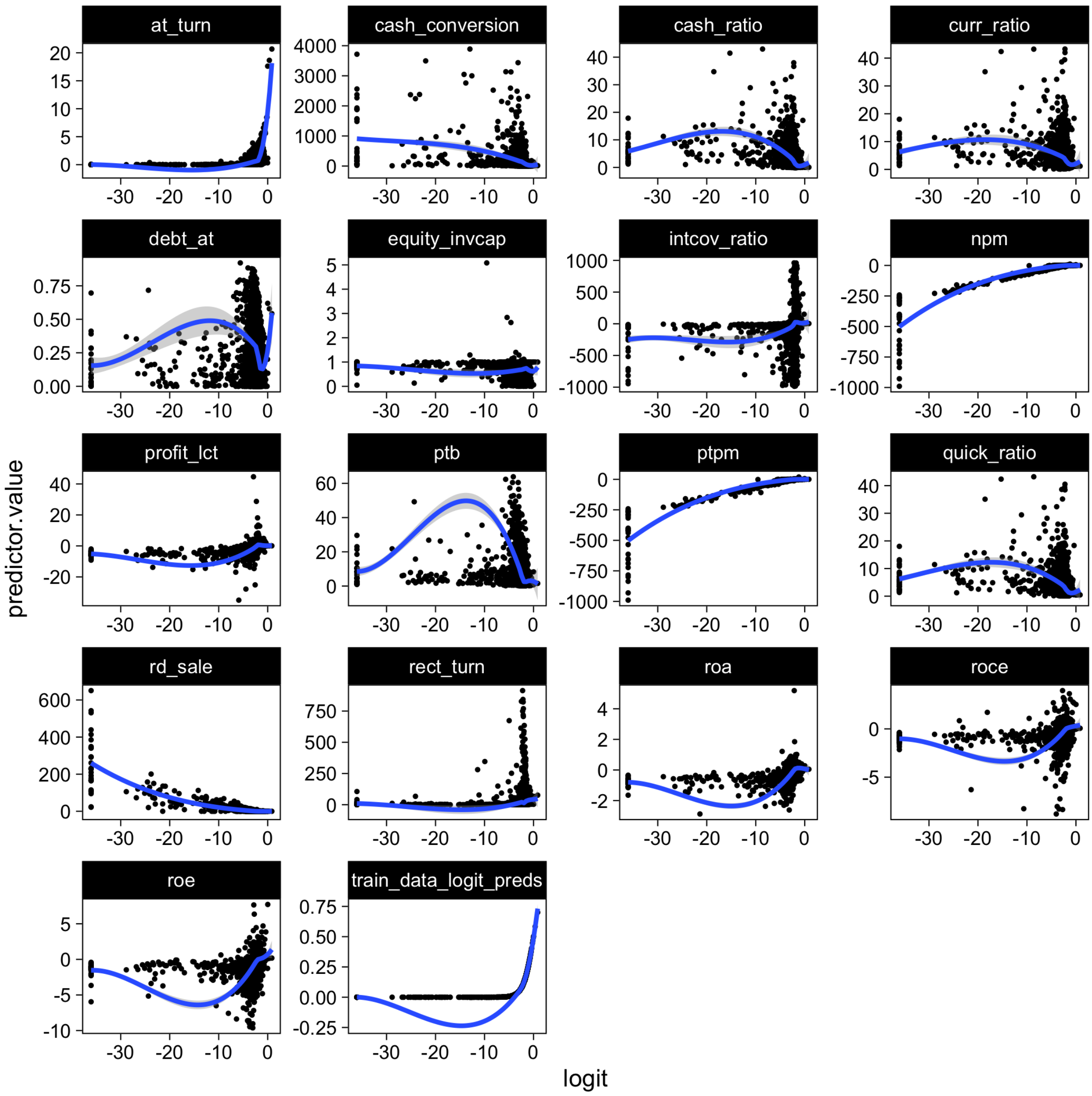


Figure A1.2: Plot showing the standard residuals of the logistic regression. Values further from zero indicate a higher residual. Plot color indicates whether the acquirer was successful.

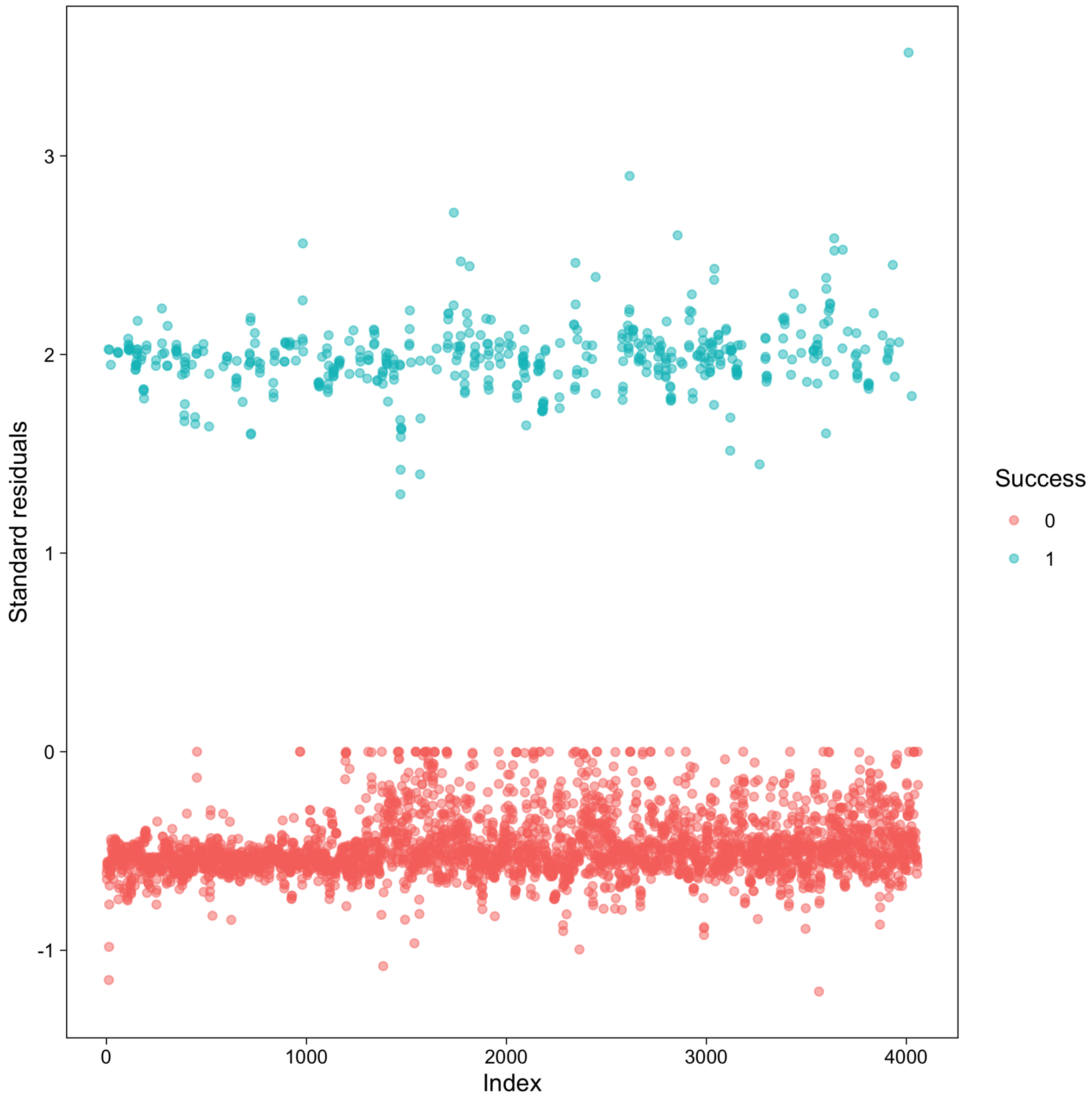
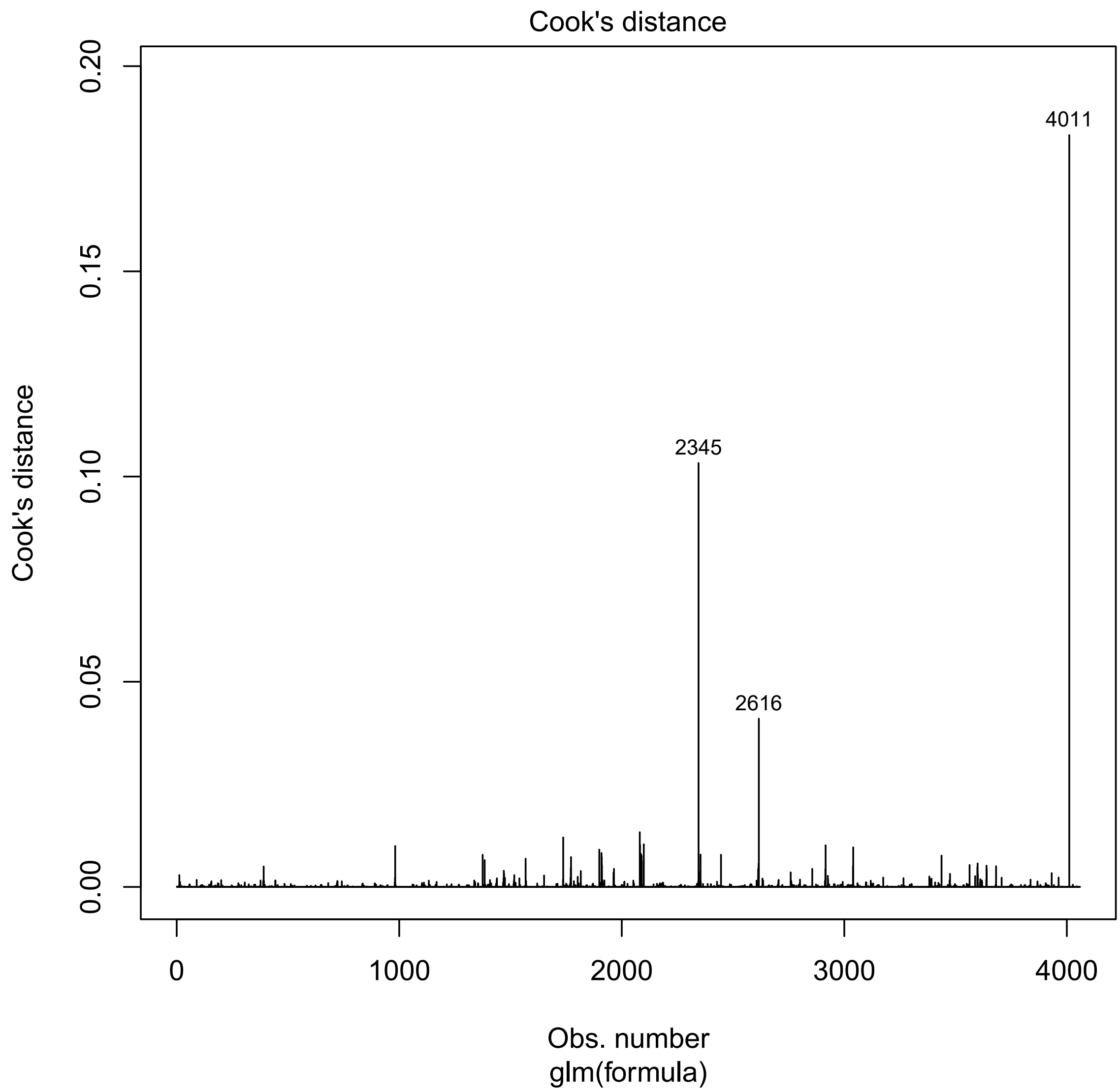


Figure A1.3: Plot showing Cook's distance for the logistic model.



A2 Partial dependence plots

Figure A2.1: Plot showing the random forest model's partial dependence plots for all predictors against the logit. One predictor is used at a time. Drawn at a resolution of $n = 30$.

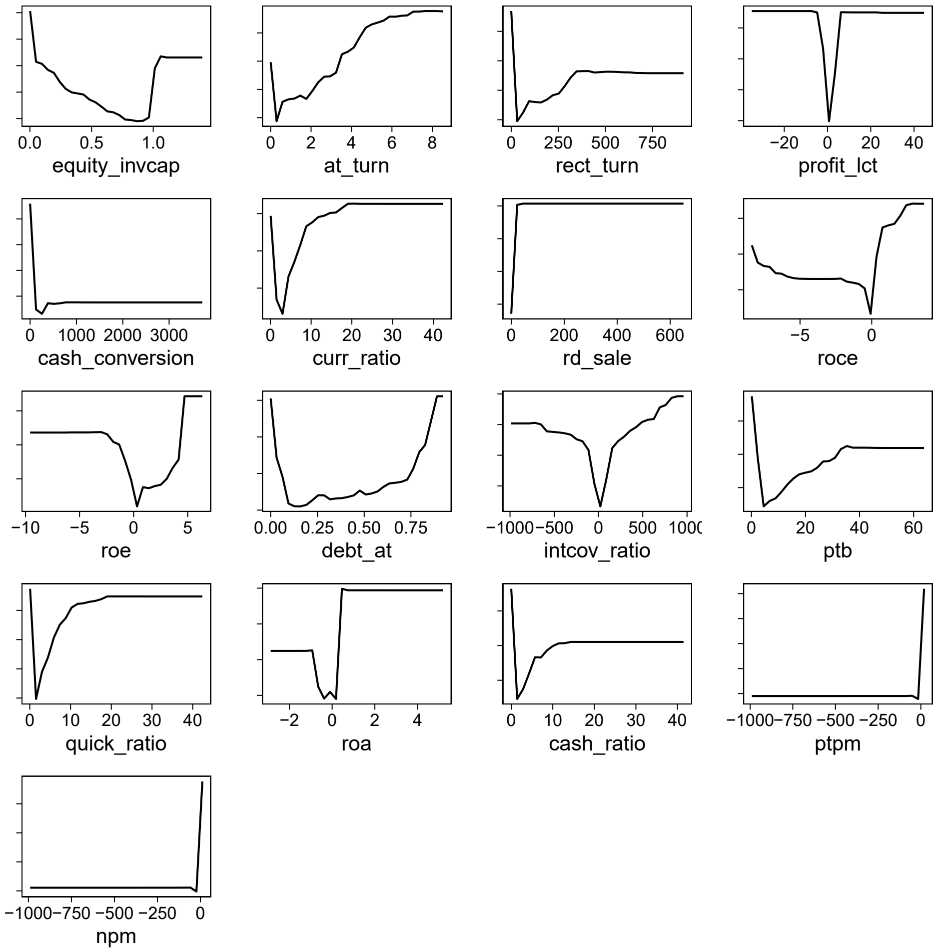
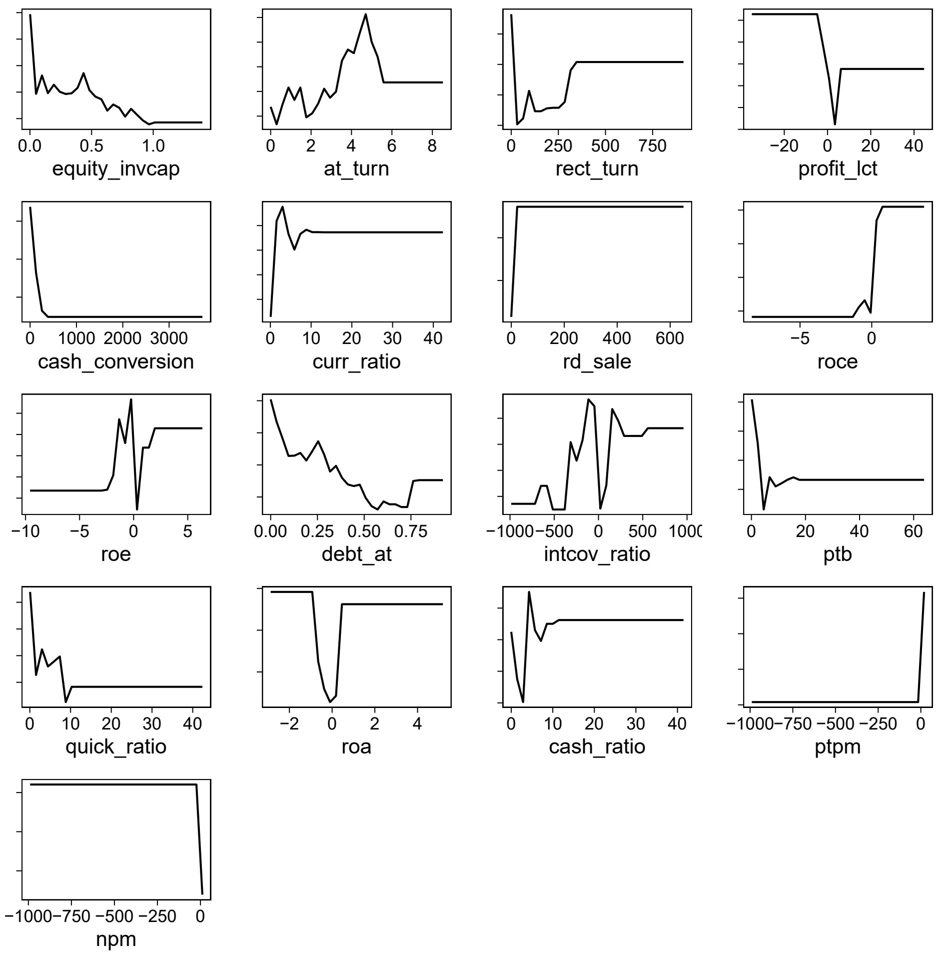


Figure A2.2: Plot showing the gradient boosting machine's partial dependence plots for all predictors against the logit. One predictor is used at a time. Drawn at a resolution of $n = 30$.



A3 Correlation matrix

Figure A3.1 and Table A3.1 show the correlation matrix for the predictors used in this thesis.

Figure A3.1: Correlation matrix between the predictors. Color scale indicating correlation coefficients from -1 to 1.

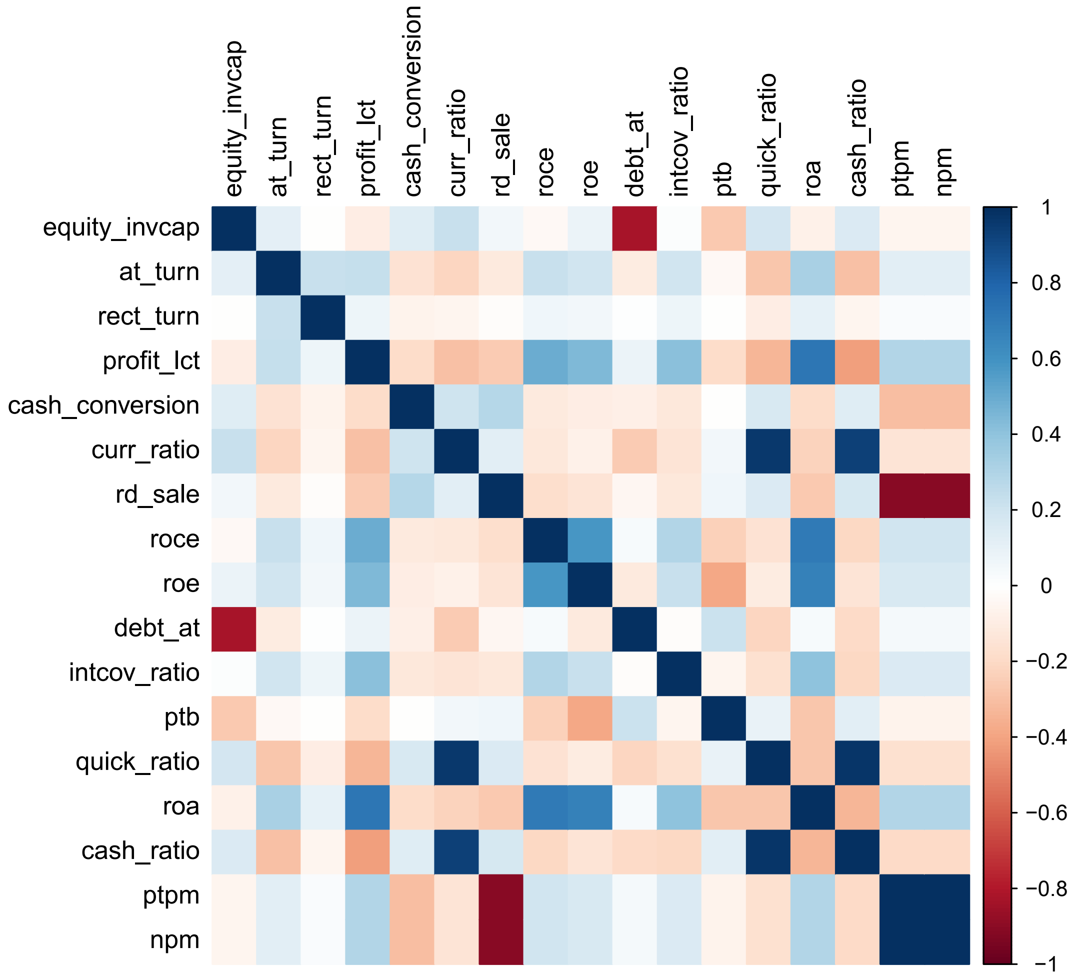


Table A3.1: Correlation matrix showing the numerical values of correlation coefficients between predictor variables.

	equity_invcap	at_turn	rect_turn	profit_lct	cash_conversion	curr_ratio	rd_sale	roce	roe	debt_at	intcov_ratio	ptb	quick_ratio	roa	cash_ratio	ptpm
equity_invcap	1.00	0.11	-0.00	-0.10	0.14	0.23	0.05	-0.03	0.09	-0.82	0.02	-0.26	0.19	-0.07	0.16	-0.05
at_turn	0.11	1.00	0.22	0.24	-0.16	-0.22	-0.12	0.23	0.19	-0.11	0.20	-0.04	-0.28	0.32	-0.29	0.13
rect_turn	-0.00	0.22	1.00	0.07	-0.06	-0.06	-0.02	0.06	0.05	0.00	0.07	-0.00	-0.10	0.11	-0.06	0.02
profit_lct	-0.10	0.24	0.07	1.00	-0.18	-0.29	-0.26	0.49	0.44	0.08	0.41	-0.18	-0.33	0.72	-0.42	0.29
cash_conversion	0.14	-0.16	-0.06	-0.18	1.00	0.21	0.28	-0.11	-0.10	-0.09	-0.12	-0.00	0.16	-0.19	0.13	-0.31
curr_ratio	0.23	-0.22	-0.06	-0.29	0.21	1.00	0.13	-0.12	-0.07	-0.26	-0.14	0.05	0.97	-0.23	0.93	-0.14
rd_sale	0.05	-0.12	-0.02	-0.26	0.28	0.13	1.00	-0.17	-0.14	-0.04	-0.13	0.07	0.15	-0.27	0.18	-0.91
roce	-0.03	0.23	0.06	0.49	-0.11	-0.12	-0.17	1.00	0.59	0.03	0.29	-0.24	-0.16	0.70	-0.20	0.19
roe	0.09	0.19	0.05	0.44	-0.10	-0.07	-0.14	0.59	1.00	-0.11	0.22	-0.38	-0.10	0.67	-0.15	0.16
debt_at	-0.82	-0.11	0.00	0.08	-0.09	-0.26	-0.04	0.03	-0.11	1.00	-0.02	0.22	-0.22	0.03	-0.19	0.05
intcov_ratio	0.02	0.20	0.07	0.41	-0.12	-0.14	-0.13	0.29	0.22	-0.02	1.00	-0.05	-0.17	0.41	-0.20	0.15
ptb	-0.26	-0.04	-0.00	-0.18	-0.00	0.05	0.07	-0.24	-0.38	0.22	-0.05	1.00	0.09	-0.27	0.13	-0.07
quick_ratio	0.19	-0.28	-0.10	-0.33	0.16	0.97	0.15	-0.16	-0.10	-0.22	-0.17	0.09	1.00	-0.27	0.98	-0.17
roa	-0.07	0.32	0.11	0.72	-0.19	-0.23	-0.27	0.70	0.67	0.03	0.41	-0.27	-0.27	1.00	-0.33	0.30
cash_ratio	0.16	-0.29	-0.06	-0.42	0.13	0.93	0.18	-0.20	-0.15	-0.19	-0.20	0.13	0.98	-0.33	1.00	-0.19
ptpm	-0.05	0.13	0.02	0.29	-0.31	-0.14	-0.91	0.19	0.16	0.05	0.15	-0.07	-0.17	0.30	-0.19	1.00