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Takeover prediction

A study in predicting takeover targets in Sweden

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Abstract

Takeovers are in general associated with bid premiums, giving rise to substantial stock returns for shareholders. This thesis investigates whether it is possible to accurately predict takeovers of Swedish firms using public information, as this would provide an opportunity to exploit bid premiums. We first employ a logit model to identify takeover characteristics of Swedish listed firms between 2005-2014 and second use this estimated model to predict takeover targets in 2015. Even though few characteristics of Swedish targets are identified, we find conclusive evidence that targets are smaller in size and suggestive evidence that targets belong to industries with previous takeover activity. However, given these limited findings, the overall results of the predictive ability of the model therefore suggest that constructing a statistical model to correctly predict Swedish takeover targets is not possible using the methods currently employed in takeover prediction studies. The findings are in line with similar studies based on American and British settings.

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1. Introduction

When a company is acquired on the stock market the shareholders of the target company, the selling firm, often receive large returns from the takeover bid due to the fact that the acquiring company, the buying firm, bids above the current market capitalization of the target (see, e.g. Goergen & Renneboog, 2004; Campa & Hernando, 2004). This particular phenomenon is referred to as a bid premium. Various explanations for why shareholders benefit from takeovers exist, with the most common being by replacing inefficient management (Grossman & Hart, 1980; Jensen, 1988; Morck, Shleifer & Vishny, 1988; Rappaport, 1990) and by exploiting synergies (Bradley, Desai & Kim, 1983). Since shareholders in general gain from owning companies that are taken over, there seems to be a valid investment strategy to invest in companies that are likely to be acquired.

Numerous empirical studies have examined differences between firms that are subjected to takeovers and firms that are not, but with overall varying results (see e.g. Manne, 1965; Hasbrouck, 1985; Lang, Stulz & Walkling, 1989; Shleifer & Vishny, 2003). While some studies have focused on the characteristics of targets, other studies have instead researched the possibility of building such models that would be able to predict takeover targets better than the stock market in an American and British setting. The first studies in this area in the 1970s (Simkowitz & Monroe, 1971; Stevens, 1973; Castagna & Matolcsy, 1976; Belkaoui, 1978) claim to have constructed models with 60% to 90% accuracy in predicting takeover targets up to 12 months before the bid announcement. The results would indicate a prediction ability far greater than the stock market itself as for instance Dodd and Rudback (1977) and Asquith (1983) have found that the stock market only identifies takeover targets during a period very close to the actual announcement of the bid. More recent studies on the other hand (Palepu, 1986; Ambrose & Megginson, 1992; Powell, 1997; Cudd & Duggal, 2000), have corrected statistical flaws of earlier studies and have instead only been able to construct models with much lower prediction rates, leading to close to zero abnormal returns.

This thesis investigates what characteristics differentiate firms that are taken over from firms that are not taken over and if it is possible on the basis of these characteristics to correctly predict future takeover targets. We will follow the methodology of Palepu (1986) to construct a logit model to predict takeover targets.

1.1. Statement of the problem and research questions

Our intention is to expand the research of Palepu (1986), to first estimate the factors that distinguish takeover targets from non-targets on the Swedish stock market using a set of financial and industrial variables and second use these estimations to test the predictive ability of the model on another set of Swedish listed firms. With respect to this, the research questions read as follows:

> *What are the characteristics of takeover targets in a Swedish setting? Furthermore, is it possible to construct a model based on these characteristics to predict future takeover targets on the Swedish stock market?*

1.2. Contribution

The intended contributions of this thesis are two-fold. First, we focus on the period after the adoption of IFRS in 2005, which could improve the ability to predict takeover targets as studies have shown that information provided under IFRS is more value-relevant for investors (Barth, Landsman & Lang, 2008). Second, while most prior literature has focused on the US market (Simkowitz & Monroe, 1971; Dietrich & Sorensen, 1984; Palepu, 1986; Ambrose & Megginson, 1992; Cudd & Duggal, 2000) and the UK market (Barnes, 1990; Powell, 1997; Barnes, 1999; Powell, 2001; Powell, 2004), we specifically look at the Swedish setting, which has been relatively underexplored so far. Moreover, given that the models of previous studies are found to have low prediction rates and only have identified a few significant characteristics but with low explanatory power, an interesting area is to examine whether the high accounting quality in Sweden (Rajan & Zingales, 1996) can affect the prediction rate of the model. Rossi and Volpin (2004) for instance have found the quality of the accounting to be an important factor in predicting takeover targets.

1.3. Scope

We limit our study to non-financial companies listed on the Nasdaq OMX Nordic Stockholm during the period 2005-2014 for the estimation of the model and during 2015 for the prediction test of the model. In this thesis, takeovers are defined as all completed bids on the Nasdaq OMX Nordic Stockholm that proceed a majority share of the target company.

1.4. Disposition

The rest of the study is divided into nine sections. Section 2 reviews the theories in use and these are definitions of takeovers, takeover theory, bid premiums and takeover prediction models. Section 3 presents the hypotheses used in the thesis and connects them to previous literature. Section 4 explains the methodology in use, describes how the sample was selected and establishes both the regression models and the prediction model. In section 5 the results from descriptive statistics, the regression models and the prediction model are presented. Section 6 describes in detail the analysis of the results and how we test our results in different ways. Section 7 concludes the thesis. A discussion on the limitations of the study is presented in section 8. Finally, in section 9 suggestions for further research are established.

2. Theory and literature review

The theories and literature on which we base our study will be presented in this section. First, the definition of and motives for takeovers and merger and acquisition (M&A) activity will be reviewed in order to establish a basis of theory to build our hypotheses on. Second, we will consider studies on the rationale to the existence of bid premiums to understand the purpose for building takeover prediction models. Finally, previous takeover prediction and bankruptcy studies will be discussed to provide guidance for our own research.

2.1. Theoretical paradigm

2.1.1. Definition of a takeover

A variety of definitions of takeovers exist, yet with very similar underlying explanations. A common denominator for the definitions is that they refer to transactions of controlling interest between two firms. DePamphilis (2010) defines takeovers as "generic terms for a change in the controlling ownership interest of a corporation". It can refer to either an acquisition or a merger. An acquisition occurs when the acquiring company buys the controlling interest in the target and when the target is not integrated in the organizational structure of the acquirer, but instead continues to operate as a legal subsidiary (DePamphilis, 2010). A merger occurs when two or more companies join to form one company, implying that the target company instead is integrated in the organizational structure of the acquirer and hence ceases to exist as an operating legal entity (DePamphilis, 2010). However, note that in this paper, no distinction between different types of takeovers will be made.

2.1.2. Takeover theory

In order to be able to predict takeovers, it is effective to look at why takeovers occur. Over the years, several empirical studies have examined the motives behind M&A and the characteristics of takeover targets. These studies will serve as the foundation on which to build our hypotheses and prediction model on. Trautwein (1990) reviews the theories of merger motives and argues that merger motives can be classified into three categories: Merger as rational choice, merger as process outcome and merger as macroeconomic phenomenon. In this thesis, the categories created by Trautwein (1990) will form the basis for the categories that we define. We will categorise them according to our hypotheses as: motives based on creating value and motives based on economic theory and macroeconomic factors. Trautwein (1990) also suggests a third category, mergers as process outcome, with motives based on psychological ground. Theories in this category argue that factors like, for instance, prestige, compensation and hubris drive managers to acquire other firms. However, since motives based on these grounds are difficult to proxy and measure with variables, they have been relatively unexplored in takeover prediction model studies. We will therefore not include this category in our scope of takeover motives, but still think that it should be mentioned as these theories include explanations very different from the other two categories.

Theories on mergers based on creating value is perhaps the most commonly researched reason for why mergers occur. The category suggests that managers of acquiring firms look at specific ratios and measures based on public information to identify attractive targets. Attractive in this case usually refers to opportunities where the acquiring firm can create value by exploiting favourable characteristics of the target. Previous literature suggests a number of features that indicate when these opportunities are present. Two common denominators for these types of theories are inefficiency and undervaluation. For example, Hasbrouck (1985) finds that American targets have much lower valuations than acquiring firms. Later research by Lang et al. (1989) support these findings and the authors argue that acquiring firms create value in takeovers by exploiting synergies or by more efficiently use the target's resources. It could also be the case that acquiring firms can exploit possibilities in targets with high growth opportunities but with low resources that before the takeover made the target incapable of realising its growth potential (Powell, 1997). In addition, Shleifer and Vishny (2003) study differences in valuations between targets and non-targets and argue that one reason for why mergers occur is because firms with high valuations on their stocks exploit this opportunity and use their stock to buy targets with low valuations.

Another commonly researched motive is that firms gain from mergers by replacing inefficient management, first explored by Manne (1965) but also supported by later studies (Grossman & Hart, 1980; Jensen, 1988; Morck et al., 1988; Rappaport, 1990). In addition, Jensen and Ruback (1983) develop in their study a management competition model that justifies mergers on the basis that value is created through managerial synergies. The logic is that firms acquire underperforming and hence cheap targets and then replace the management in order to create value. Furthermore, similar motives are linked to ownership structure. Shleifer and Vishny (1986) reason that monitoring of management is more successful in firms with shareholders owning large blocks of shares, called blockholders. Using the same rationale of inefficient management theories, one can conclude that firms with few large blockholders should be more vulnerable to takeovers since acquirers can exploit this inefficiency and create value.

Asset structure is also a frequently researched characteristic of takeover targets. Hasbrouck's (1985) research shows that target firms are smaller in size than non-targets. Hasbrouck (1985) further argues that this is because the integration of larger firms is much costlier than the integration of smaller firms. Additionally, Stulz and Johnson (1985) find that the tangible assets to total assets ratio is highly important for firms' availability to debt. The suggested conclusion is that firms seek to acquire targets with high debt capacities because new debt can be used to finance new investment opportunities which can create higher firm value.

Theories based on economic theory and macroeconomic factors offer other explanations for why mergers occur. Theories within this category explain mergers as a result of larger macroeconomic factors or trends. Gort (1969) was one of the first to establish theories within this category and his findings indicate that M&A activity occurs in industries subjected to economic shocks or other disturbances, e.g. deregulations and disruptive technology. More recent research also supports the theory that M&A activity is mainly driven by macroeconomic and industry shocks (see, e.g. Mitchell & Mullherin, 1996; Maksimovic & Phillips, 2001; Rhodes-Kropf, Robinson & Viswanathan, 2005).

2.1.3. Bid premiums

Having laid out the foundation to what takeovers are and why they occur, theories on bid premiums broaden our understanding of why takeover prediction models are of interest. Various empirical studies have shown that target company shareholders on average gain significant abnormal returns following an announcement of a takeover offer on the U.S.

(Schwert, 1996; Andrade, Mitchel & Stafford, 2001) and UK and European markets (Goergen & Renneboog, 2004; Campa & Hernando, 2004). For example, Andrade et al. (2001) find that the shareholders of the target firm in general obtain a cumulative abnormal return of 16% between the day before the announcement until the day after the announcement and if the period is extended to 20 days before the announcement to the closing of the deal, the same return is 23.8% with statistical significance at the 1% level. To the best of our knowledge there are no research papers that examine the bid premiums solely on the Swedish stock market. However, and in high relevance to this study there is one master's thesis from the Stockholm School of Economics which investigates the announced bid premiums using Swedish data. Aronsson (1995) performs a study on the Swedish stock market, which indicates that target shareholders in successful takeover transactions earned an average of 20% during 1980-1994.

2.2. Description of previous prediction model studies

The field of studies in takeover prediction models used to exploit bid premiums is thoroughly explored yet concentrated, as mentioned earlier, to an American and British setting. Numerous studies exist, and the most prominent ones will be reviewed in the following subsections.

2.2.1. Palepu (1986)

Palepu (1986) is perhaps the most prominent in the field and serves as the main source for many other related studies. The study analyses previous takeover prediction research (Simkowitz & Monroe, 1971; Stevens, 1973; Castagna & Matoscy, 1976; Belkoui, 1978) and examine whether it is possible to earn abnormal returns by using prediction models. Palepu (1986) identifies three general faults of earlier models that explain their high prediction rates. First, the models use non-random sampling methods when estimating the models which increases the biases of the estimated acquisition probabilities. Second, the use of an equal number of targets and non-targets in the prediction models makes the sample incapable of representing the entire population which leads to prediction rate errors. Third, earlier research uses arbitrary cutoff probabilities, without concerning factors like the distribution of non-targets and targets of the population. Palepu (1986) addresses and corrects these faults and conducts a study on firms on the New York and American Stock Exchange in the mining and manufacturing sectors during 1971-1979. Palepu (1986) finds significant evidence at the 5% level that takeover targets, in comparison to non-targets, are smaller in size, have lower excess return on their stock, lower sales growth, lower leverage and do not belong to industries with previous M&A activity. In addition, Palepu (1986) finds significant results that takeover targets have a mismatch between sales growth and resources. The results further do not support differences in price-earnings ratios (p/e-ratios), market-to-book ratios, return on equity (ROE) nor liquidity among targets and non-targets, on the contrary to what was expected. However, the most significant model only has a 12.45% explanatory power, indicating that only 12.45% of a target's prediction rate is explained by the model. The model correctly predicts 24 targets out of a total of 30 but at the same time only correctly classifies 486 non-targets out of a total of 1,087. This implies that number of type I errors, classifying a target as a non-target, are rather small while the number of type II errors, classifying a non-target as a target, are significant.

2.2.2. Barnes (1990) and Barnes (1999)

Barnes (1990) argues that there are several general reasons for why prediction models are not stable across different periods of time, of which the two main factors are macroeconomic factors and changing motives for acquisitions. Barnes (1999) introduces certain methodological improvements to some of the issues raised in his previous research and by Palepu (1986). Barnes (1999) proposes an improvement in form of industry-relative ratios, aiming to increase the stability of the model and adjust for time-effects and industry-effects on the financial variables. However, the results show that the industry-relative ratios were not an improvement. Barnes (1999) argues that one problem with the industry-adjusted variables is that they are very sensitive to industries with abnormal data and require all industries to be properly represented in the sample.

2.2.3. Ambrose and Megginson (1992)

Ambrose and Megginson's (1992) research builds on the model used by Palepu (1986) by combining his hypotheses with two new ones. The first new hypothesis is based on ownership structure and more specifically insider and institutional shareholding. The other added hypothesis is asset structure where a variable of the ratio of tangible assets to total assets is used as a proxy. Overall, the prediction rates of the three estimated models are inferior to the models developed by Palepu (1986) and only one of them is significant. Yet, the model supports the hypotheses that smaller firms and firms with high ratio tangible assets to total assets are likely to be takeover targets. Ambrose and Megginson (1992) also find evidence that takeover targets have a smaller change in institutional shareholding the quarter before a bid announcement than non-targets.

2.2.4.Powell (1997) and Powell (2001)

Powell (1997) studies first the possibility to develop a model of takeover prediction and second if the model holds over time. Over all, the explanatory power of the model is, as in similar studies weak. However, the study finds that the lower the liquidity of a firm, the lower the size of a firm and the higher the tangible assets of a firm, the higher the likelihood of becoming a target. Additionally, the results indicate that the prediction rate of the model is not robust over time and different variables are significant for different periods of time, indicating a need for time-adjustments in the model.

The main difference between Powell (2001) and Palepu (1986) is that Powell focuses on building a portfolio with abnormal return rather than building a statistical model. Hence, he uses an equal number of targets and non-targets in the sample, something Palepu (1986) argues violates the statistical correctness of the model. The difference is that Powell chooses the cutoff probability based on maximizing the ratio of targets correctly classified, whilst other papers have based it on minimizing the sum of type I errors and type II errors. The cutoff probability in the study is therefore much higher than the cutoff probability of Palepu (1986), ranging on average around 0.5. Although Powell (2001) reduces the type II errors substantially (on average 90% of the non-targets are correctly classified), the model also only correctly classifies 2% of the targets when tested on the population, leading to an overall low predictive ability. Hence, the misclassification of targets reduces the abnormal return close to zero.

2.2.5.Cudd and Duggal (2000)

As in Palepu (1986), Cudd and Duggal (2000) uses a logit regression model to predict takeovers. The study replicates the methodology of Palepu (1986) but in addition explores the possible impact of industry-specific distributional characteristics of firm specific variables in the context of takeovers. Cudd and Duggal (2000) do this by adjusting each variable for industry-specific distribution. The study finds supporting evidence that targets are lower in size, have a growth-resource-mismatch and have lower ROE, leverage, liquidity and sales growth. The results also support the fact that firms that belong to industries with previous M&A activity are more likely to become takeover targets. The result after adjusting for industry-specific dispersion is that the model has a higher classification accuracy than the model without industry adjustments and comes with a p-value indicating statistical significance. Cudd and Duggal (2000) therefore conclude that industry-adjusted variables provide a better model.

2.2.6. Other related prediction studies

In addition to the literature discussed above there is another relevant takeover prediction study worth mentioning. The study is a master's thesis from the Stockholm School of Economics by Hillström and Jacobsson (1998) who test a prediction model on a sample of Swedish firms between 1985-1995 and find that firms that have lower p/e-ratios and more concentrated ownership structure are more likely to become takeover targets. However, the study finds that it is difficult to predict future takeover targets in a Swedish setting since the explanatory power of the model is insignificant. Therefore, it is interesting to see if these findings are consistent in a more modern setting.

There are also a number of bankruptcy prediction studies that employ methodologies similar to those in takeover prediction (see e.g. Altman, 1968; Ohlson, 1980; Zmijewski, 1984; Chava & Jarrow, 2004). Methodologies for establishing the data collection, sampling process and regression model are similar to those used in bankruptcy prediction. Therefore, this paper will use bankruptcy prediction as a complement to takeover prediction studies for a broader understanding of the methodology used in constructing prediction models, especially regarding the case of sample selection. In short, there are different methods often used in bankruptcy prediction for collecting the control sample, the sample of non-bankrupted companies, or in our case the sample of non-targets. A more in-depth description of how we use the methodology in bankruptcy prediction to fully grasp the different sampling techniques and other methodological issues will be presented in section 4.

3. Hypotheses

Following the literature review, the hypotheses explored in this study will be presented in this section which serve as the base from which we choose our independent variables. The hypotheses are based on the hypotheses examined by Palepu (1986) as well as two additional hypotheses: Ownership structure and capital structure explored by Ambrose and Megginson (1992) to be significant in predicting takeover targets.

3.1. Price-earnings hypothesis

The hypothesis relates to theories on undervaluation and inefficiencies. The logic behind the hypothesis is that in order to lower its own p/e-ratio, firms want to acquire targets with low p/e-ratios since the ratio is an indication of the valuation of the firm. Shleifer and Vishny (2003) support this theory and argue that when a firm has high p/e-ratios, they have strong incentives to use their overvalued stock and buy targets with low p/e-ratios. The goal of such a deal is to realise a direct capital gain, since the acquirer expects that earnings for the new combined firm will be valued at the higher p/e-ratio of the acquiring firm. Moreover, Lang et al. (1989) argue that the largest benefits from takeovers occur when the acquiring firm has a high valuation and the target firm has a low valuation. The hypothesis therefore suggests that firms with low p/e-ratios are likely to be acquired by firms with high p/e-ratios. Several prediction models including Dietrich and Sorensen (1984), Palepu (1986), Ambrose and Megginson (1992), Barnes (1999), Cudd and Duggal (2000) and Brar, Giamouridis, and Liodakis (2009) test this hypothesis but with varying results.

H_1: Firms with low p/e-ratios are more likely to become takeover targets than firms with high p/e-ratios.

3.2. Market-to-book hypothesis

Similar to the previous hypothesis, this hypothesis simply reflects firm undervaluation of the targets and is based on the theory that firms are expected to acquire targets with low market-to-book ratios since these firms are considered to be cheaper. In research, Tobin's q is also a common measure for undervaluation with the market-to-book ratio being a proxy for this metric. For example, Hasbrouck (1985) studies differences in Tobin's q between American targets and non-targets and finds the q of targets to be considerably lower. Lang et al. (1989) find that American firms with high q values that acquire firms with low q values are more rewarded on the stock market than firms with low q values acquiring targets with high q values. In addition, more recent research by Rhodes-Kropf et al. (2005) indicates that firms with high market-to-book ratios tend to acquire firms with low market-to-book ratios in order to lower their own market-to-book ratio. We therefore expect that firms with low market-to-book values are more exposed to takeovers.

H_2: Firms with low market-to-book ratios are more likely to become takeover targets than firms with high market-to-book ratios.

3.3. Inefficient management hypothesis

The hypothesis is used to investigate theories indicating that one motive for acquisitions is the replacement of managers who fail to maximize the use of its firm's assets. Manne (1965) was among the first to develop theories about corporate control and finds that managers of bidding firms are commonly characterized by a value-maximizing practice in which replacement of inefficient management is a method used to create value. These findings have been further supported by other studies, e.g. Asquith (1983), Morck et al. (1988) and Morck et al. (1990). Another central study for this hypothesis is the management competition model by Jensen and Ruback (1983) which suggests that managerial synergies is a common method for firms to generate value in acquired firms. More studies have also shown that a reason for why shareholders benefit from acquisitions is the replacement of inefficient management (Grossman & Hart, 1980; Jensen, 1988; Rappaport, 1990). Hence, the higher the inefficiency of the management, the higher the likelihood of being a takeover target. The majority of previous takeover target prediction studies, including e.g. Palepu (1986), Ambrose and Megginson (1992), Barnes (1999), Cudd and Duggal (2000) and Powell (2001) explore this hypothesis.

H_3: Firms with inefficient management are more likely to become takeover targets than firms with efficient management.

3.4. Size hypothesis

Size is a commonly studied hypothesis to examine the importance of asset structure in takeovers. Acquisitions of larger firms are believed to be related with larger transaction costs, e.g. cost of integrating the target into the organization and costs of dealing with defence mechanisms of the target. This assumption is consistent with the research of Hasbrouck (1985), suggesting that the cost of acquiring a larger firm is relatively higher than the costs of acquiring a smaller firm. Given the increasing costs, bigger companies are assumed to have fewer bidders. Therefore, the hypothesis assumes that the bigger the size, the lower the likelihood of the firm being acquired. Firm size is for instance a hypothesis Palepu (1986) suggests being significant in explaining takeover likelihood. It is also a hypothesis many other takeover target prediction studies explore and find support for, e.g. Ambrose and Megginson (1992), Powell (1997) and Cudd and Duggal (2000).

H_4: Smaller firms are more likely to become takeover targets than larger firms.

3.5. Industry disturbance hypothesis

The hypothesis is related to takeover motives based on macroeconomic factors. The research of Gort (1969) is the foundation of the hypothesis as it suggests that takeovers are prone to follow economic and industrial trends, giving rise to systematic fluctuations in M&A activity. This is because changes in important factors of an industry create increasing or decreasing M&A activity. Gort (1969) argues that the economic disturbance of an industry creates differences in the valuations of the firms in that industry, which fuel mergers. This is because information about the past, information used to value firms, becomes less valuable when the structure of an industry changes. Mitchell and Mulherin (1996) also support the industry disturbance theory, arguing that industry specific acquisition rates (the number of acquisitions in an industry to the total number of firms) are driven by economic shocks of the industry. We would therefore expect takeovers in a certain industry to come in waves, i.e. one takeover will be followed by more takeovers in the same industry.

H_5: Firms in industries with recent M&A activity are more likely to become takeover targets than firms in industries with no recent M&A activity.

3.6. Growth-resource-mismatch hypothesis

A mismatch between growth and assets is assumed to be a good indication of inefficiencies and the hypothesis thus suggests that either firms with high assets and low growth or firms with low assets and high growth are likely to be takeover targets. The hypothesis is supported by the research of Cosh, Hughes and Singh (1980) and Levine and Aaronovitch (1981). Furthermore, high growth, low assets firms in particular have been researched by Myers and Majluf (1984). One explanation could be that firms seek to acquire other firms with an opposite growth-resource mismatch because they believe either that the resources in the target can be more efficiently invested in the firm's projects or that the target's projects can be more efficiently financed by the firm's high resources, i.e. financed by a lower cost of capital. Palepu (1986), Ambrose and Megginson (1992) and Powell (1997) among others test the hypothesis and find it to potentially be a contributing factor in predicting takeover targets.

H_6: Firms with a mismatch between growth and resources are more likely to become takeover targets than firms with a match between growth and resources.

3.7. Institutional shareholding hypothesis

The institutional shareholding hypothesis is linked to theories on creating value in mergers through exploiting the ownership structure of the targets. It is less examined than the other hypotheses. The first studies in the field explore the effect of absolute levels of institutional shareholding. Shleifer and Vishny (1986) for example expect that high levels of large blockholders, usually institutional shareholders, lead to better monitoring of management. It implies that firms with low levels of institutional shareholding should be performing worse than firms with high levels. Based on the same logic regarding takeover theories on inefficiencies, firms with low levels of institutional shareholding should therefore be subjected to more takeover attempts. Ambrose and Megginson (1992) test this hypothesis but instead argue that it is the change in institutional shareholding rather than the absolute level that characterizes targets as they find a significant negative correlation between net change in institutional shareholding the quarter before an announcement bid and takeover likelihood. Ambrose and Megginson (1992) hypothesise that this could be because of institutional shareholders selling shares as soon as a takeover attempt is on the agenda and their results further indicate that the change is particularly strong in the five largest institutional shareholders.

H_7: Firms with a negative change in institutional shareholding are more likely to become takeover targets than firms with a positive change on institutional shareholding.

3.8. Tangible fixed assets hypothesis

To further examine the takeover motives based on the asset structure of a firm, the following hypothesis will be included. Asset structure and in particular the ratio of tangible assets to total asset is an area Stulz and Johnson (1985) indicate to be important for firm's debt capacity. The argument is that having a high level of tangible assets increases the availability of secured debt which can be used to create higher value in firms as more investments can be realized. This is because tangible assets can be used as collateral, whereas intangible assets are much harder to use as collateral. Myers and Majluf (1984) also examine the effect of capital structure on financial policies in companies and find that it is of notable importance. We would therefore expect that firms with high debt capacity, i.e. firms with high tangible assets relative to total assets, are more likely to become takeover targets since acquiring firms can take advantage of the possibility to leverage the target in order to be able to undertake new investment opportunities. In addition, the findings of Ambrose and Megginson (1992) and Powell (1997) support these theories as they find a significantly positive correlation between the ratios fixed assets to total assets and the likelihood of becoming a target.

H_8: Firms with a high ratio of tangible assets to total assets are expected to be more likely to be takeover targets than firms with low ratios of tangible assets to total assets.

4. Methodology

In this section we will first introduce our sample selections and the procedures followed to collect them. Second, we will present data adjustments. Lastly, we present our regression models and all the included variables and how these are calculated, followed by an introduction to the prediction model used to test the feasibility to predict future takeover targets.

4.1. Sample – Targets and Non-target firms

When constructing a prediction model, two samples have to be generated. The first sample will be used to estimate the coefficients of the selected variables using the logit model. This sample is called the estimation sample. The second sample will be used to test the predictive ability of the estimated model. This sample is called the hold-out sample. For both samples, both targets and non-targets have to be included. The following subsection will explain the procedure for selecting these samples.

4.1.1. Sample selection – Target firms

For the estimation sample, a number of public Swedish firms listed on the Nasdaq OMX Nordic Stockholm between 2005 and 2014 are used. Out of this sample, firms that are subject to a completed takeover bid during the period are used for the estimation of target firms. The sample is constructed out of information from Thomson Reuters Deal Screen. Through a selection process consisting of four criteria our sample is reduced to the final target sample size. When screening for total number of bids between 2005 and 2014 a list consisting of 684 announced bids is generated.

First, we exclude all bids that are not completed bids, which means that bids that are "Intended", "Rumours" and "Withdrawn" are removed from the sample. This screening reduces the sample size by 186 deals. Second, given the limited number of observations of takeover targets on the Nasdaq OMX Nordic Stockholm, our sample just like Ambrose and Megginson (1992), but unlike Palepu (1986), includes firms from all industries. Another alteration is the fact that we use Nasdaq OMX Nordic Stockholm's definition of GICS industry instead of the four digits SIC industry as Palepu (1986) did. This is due to the fact that we use another database (Thomson Reuters) in which the sector definitions are different from the database used by Palepu (1986) (COMPUSTAT). The GICS definition is nevertheless approximately the same as the SIC industry definition. However, following the method of Ambrose and Megginson (1992) companies in the financial services sector are excluded from the sample. They are excluded because financial ratios for banks and insurance companies differ greatly from other industries and they could therefore potentially distort the results of the model. This includes companies that belong to GICS sector "40 - Financials", which means that the GICS industry groups "4010 - Banks", "4020 - Diversified Financials" and "4030 - Insurance" are not included in the sample. After adjusting for financial services, the sample of target firms is reduced by 44 deals.

Third, since we define our takeover targets as all completed bids that proceed a majority share of the target company, bids equal to or below 50% of the total shares are excluded from the sample. This reduces the sample by another 329 deals. Fourth, all deals that lack data points necessary for calculating our variables in Thomson Reuters Eikon are removed. After adjusting for missing data points the sample is reduced by 13 deals. The final number of targets included in the estimation sample is presented in Table 1 and consists of 76 completed bids between the years 2005-2014.

Table 1.
Target sample screening for the estimation sample

Number of announced bids during 2005-2014 on Nasdaq OMX Nordic Stockholm	**648**
Uncompleted bids	-186
Sample size	**= 462**
Financial companies	-44
Sample size	**= 418**
Percentage acquired ≤ 50%[1]	-329
Sample size	**= 89**
Data limitations[2]	-13
Total target sample size	**= 76**

[1] *A screening criterion since we are defining a takeover target as all completed bids that proceeds a majority share of the target company.*
[2] *Observations where the financial data needed to calculate the variables in the regression has not been available in Thomson Reuters have been excluded from the sample.*

For the prediction model, all targets listed in 2015 on the Nasdaq OMX Nordic Stockholm are included which includes 11 targets. The 11 targets are included in the hold-out sample.

4.1.2. Sample selection – Non-target firms

There are two methods commonly used in takeover and bankruptcy prediction model studies for choosing the control sample, the sample of non-targets in this case, to use for the estimated model and the prediction model. The first method is to start with the entire population and then draw a random sample to use in the estimation sample (see e.g. Palepu, 1986; Ambrose & Megginson, 1992; Powell, 1997; Cudd & Duggal, 2000). This is called a choice-based sample implying that all targets are included while a random selection of non-targets are included (Powell, 1997). All non-targets thus have the same probability of being selected in the sample. Moreover, given that the number of non-targets in a population is expected to be far greater than the number of targets, the method is likely to result in a sample consisting of more non-targets than targets. The method also suggest that all firms listed in the subsequent year to the final year of the studied period and not already included in the estimation sample should be included in the hold-out sample. Since the intended use of the prediction model is to use it on the entire population, the method is favourable since the distribution of the hold-out sample will most likely resemble the distribution of the entire population, with more non-targets than targets included (Palepu, 1986).

The other method commonly used is a state-based sample, also called a matched pairs sample (see e.g. Altman, 1968; Ohlson, 1980; Barnes, 1990; Crawford & Lechner 1996; & Powell, 2001). The method is based on using an estimation sample consisting of an equal number of non-targets and targets, resulting in the fact that the probability of a firm being included in the sample is based on whether the firm is a non-target or target and the distribution of non-targets and targets in the population. The same methodology is used to generate the hold-out sample, but with another set of firms. A state-based sample is suitable in a population like the population consisting of targets and non-targets since the number of non-targets are substantially more than the number of targets as it is claimed to provide the model with better estimates of the parameters than a random sample (Manski & Lerman, 1977; Manski & McFadden, 1981). However, Palepu (1986) argued that the use of the state-based method leads to a bias in the error rates in predicting targets and non-targets. The argumentation of Palepu (1986) is based on Zmijewski (1984) who examined these error states in different samples on bankruptcy prediction models and found that the state-based sample leads to oversampling of the dependent variable group which ultimately results in biased prediction error rates. This is because the method assumes an equal distribution of targets and non-targets, while the population consists of a vast majority of non-targets and very few targets. In response to the related problems of state-based sampling, Palepu (1986) argued that the sample used for estimating the model and for testing the predictive ability of the model should resemble the sample the prediction model is intended to be used on, i.e. the entire population. Therefore, in order to mitigate the problem of bias prediction rate errors described above, we will follow the methodology of Palepu (1986) and use the entire population and then draw a random sample to use in the estimation model and include the residual of firms listed in 2015 in the hold-out sample.

In using the method of choice-based sampling, we start with the entire population of firms as the dataset which consists of a sample of 266 firms not acquired as of the end of 2014. Of these firms, 220 meet the requirement of data availability and are thus included. We then randomly pick every second firm of the list to include in the estimation sample and receive a sample of 110 firms to use for the estimation of "non-target firms". Every second firm is an arbitrary chosen number, Palepu (1986) used every sixth but given our small population of firms, we have to use a higher fraction of firms to be included in the estimated model. For our hold-out sample, we use all non-financial firms on the Nasdaq OMX Nordic Stockholm in 2015 that are not included in the estimation sample and are not taken over in 2015 in order to test the prediction rate of the model which includes 110 non-targets.

Furthermore, when selecting the data for the non-targets in the estimation sample in a choice-based sample, two additional methods are generally used. One method is to choose the year of the observation for non-targets as the last year of the studied period, i.e. the year the firm is observed not to have been acquired (Palepu, 1986; Cudd & Duggal, 2002). The other method is distributing the sample of non-targets over the examined period (see e.g. Zmijewski, 1984; Ambrose & Megginson, 1992; Powell, 1997). We will employ the latter method and use a temporal matching scheme for distributing the sample over the examined period. This is the same method as Ambrose and Megginson (1992) employed. The method suggests that instead of matching an equal number of non-targets with targets for every year of observation as in a state-based sample, an equal fraction of non-targets and targets will be matched for every year. By using a temporal matching scheme for distributing the sample, our model will have a better adjustment for the effects of yearly trends on financial variables. This is an important factor to consider given the results of Powell (1997) which indicated that prediction models do not hold over time as the variance in the significance of variables are great. Moreover, Barnes (1990) argued that macroeconomic factors have large impacts on the stability over time of a prediction model. The period we are examining includes a booming economy followed by the financial crisis of 2008; times of irregular M&A activity and economic growth. The time-period studied by Palepu (1986) for instance does not include these macroeconomic phenomenon, making the method of defining the observation year of the non-target sample as the last year of the studied period less problematic.

Table 2.
Composition of the estimation sample by year

	Number of firms			
	Targets		Non-targets	
Year	Number	Percent	Number	Percent
2005	6	7.9%	9	8.2%
2006	11	14.5%	16	14.5%
2007	10	13.2%	14	12.7%
2008	9	11.8%	13	11.8%
2009	9	11.8%	13	11.8%
2010	11	14.5%	16	14.5%
2011	8	10.5%	12	10.9%
2012	3	3.9%	4	3.6%
2013	3	3.9%	4	3.6%
2014	6	7.9%	9	8.2%
Total	76		110	
Unacquired firms 2014	220			
Random selection of every second firm	-110			
Total sample	**186**			

We will as our primary method therefore use a matched sample but will also conduct a robustness check with a non-target sample according to the method used by Palepu (1986). Every non-target is randomly distributed over the period between 2005 and 2014 in order to construct the sample and give every firm an observation year for the data selection process. The final estimation sample consists of 76 targets and 110 non-targets. The composition of the estimation sample by year can be seen in Table 2 and the composition of the estimation sample by industry can be seen in Appendix 7. The final hold-out sample includes 11 targets and 110 non-targets. Regarding the hold-out sample, 2015 will serve as our observation year for the data selection process.

4.2. Data adjustments

Given that our sample includes firms from every industry on the Nasdaq OMX Nordic Stockholm (except for GICS sector "Financials" as discuss earlier in section 4.1.1), there is a potential risk of industry specific parameters affecting the financial ratios of the firms. This is one of the reasons why Palepu (1986) and other studies with a greater number of observations limited their sample to two industries. Moreover, Powell (2001) argued that a prediction model should hold across industries in order to be considered useful and that one way to increase the stability of the model is to use industry-relative ratios. In order to deal with this issue, we will follow the methodology of Cudd and Duggal (2000) and create industry-adjusted variables. Cudd and Duggal (2000) found the adjusted model compared to the original unadjusted model proposed by Palepu (1986) to have a higher number of significant variables and that more variables are consistent with the hypothesis they are based on, indicating a stronger model in predicting takeover targets. Notable is however that Cudd and Duggal (2000) only used firms from two industries. Industry-adjusted variables have also been used by Barnes (1999) and Powell (2001) in takeover prediction and Platt and Platt (1990) in bankruptcy prediction. To create industry-adjusted variables, each financial ratio will be calculated based on the following formula:

$$\mathrm{I_i} = \left(\mathrm{U_{ij}} - \mathrm{N_j}\right)/\sigma_\mathrm{j} \tag{1}$$

Where each variable is defined as: $\mathrm{I_i}$ is the industry-adjusted variable, or more specifically the deviation of the ratio from the industry average for firm i, $\mathrm{U_{ij}}$ is the unadjusted variable of firm i in industry j, $\mathrm{N_j}$ is the industry average of the variable in industry j and σ_j the standard deviation of the variable of all firms in industry j.The method adjusts the financial ratios in the model from including ratios unique to each different industry. This implies that the ratio $\mathrm{I_i}$ is a relative measure of the ratio to the industry average. To exemplify, p/e-ratios are expected to be higher for companies in the information technology sector than in the industrial sector. Hence, we would systematically see higher p/e-ratios for technological companies, regardless of if they are targets or non-targets, than we would for industrial companies. By using this method, we will be able to create relative measures of the ratios instead; leading to the study being able to use companies from different industries with different unique average levels of financial ratios. However, to see the effects of using industry-adjusted variables, a robustness test will be presented in section 5 where we run the same regression models using unadjusted variables.

4.3. The regression models

4.3.1. The main regression models

Three different logit regression models are used to estimate the independent variables. Palepu Model 1 and Palepu Model 2 are replicated models based on the first two models constructed by Palepu (1986), with the exception of year fixed effects. Year fixed effects have been included to control and to detect temporal effects following the discussion in section 4.1.2. We believe it is important to see the magnitude of these effects given our choice of sampling method that differs from the method used by Palepu (1986). Palepu Model 1 uses the variables from the first six hypotheses, with Palepu Model 2 including LEVERAGE, LIQUIDITY and GROWTH as well. The Thesis Model adds to Palepu Model 2 by also including the variables NETCHG and REALPROP first explored by Ambrose and Megginson (1992).

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

$$= \beta_0 + \beta_1 \mathrm{PE_i} + \beta_2 \mathrm{MTB_i} + \beta_3 \mathrm{AER_i} + \beta_4 \mathrm{SIZE_i} + \beta_5 \mathrm{IDUMMY_i} + \beta_6 \mathrm{GRDUMMY_i} + \text{Year Fixed Effects} + \varepsilon$$

Palepu Model 1(2)

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

$$= \beta_0 + \beta_1 \mathrm{PE_i} + \beta_2 \mathrm{MTB_i} + \beta_3 \mathrm{GROWTH_i} + \beta_4 \mathrm{LEVERAGE_i} + \beta_5 \mathrm{LIQUIDITY_i} + \beta_6 \mathrm{AER_i} + \beta_7 \mathrm{SIZE_i} + \beta_8 \mathrm{IDUMMY_i} + \beta_9 \mathrm{GRDUMMY_i} + \text{Year Fixed Effects} + \varepsilon$$

Palepu Model 2 (3)

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

$$= \beta_0 + \beta_1 \mathrm{PE_i} + \beta_2 \mathrm{MTB_i} + \beta_3 \mathrm{GROWTH_i} + \beta_4 \mathrm{LEVERAGE_i} + \beta_5 \mathrm{LIQUIDITY_i} + \beta_6 \mathrm{AER_i} + \beta_7 \mathrm{SIZE_i} + \beta_8 \mathrm{IDUMMY_i} + \beta_9 \mathrm{GRDUMMY_i} + \beta_{10} \mathrm{NETCHG_i} + \beta_{11} \mathrm{REALPROP_i} + \text{Year Fixed Effects} + \varepsilon$$

Thesis Model (4)

The definitions of variables in the models are the following: $Logit(\rho)$ is the log-odds that our dependent variable will be classified as a target (Y=1) given a specific set of values of the independent variables for a particular firm, β_0 is the intercept, β_i are the regression coefficients and ε is a disturbance term.

4.3.2. Independent variables

Our independent variables are proxies used to measure and test the hypotheses presented in section 3. A summary of all the independent variables, their related hypotheses and expected signs are presented in Table 3. In addition, given that we only have predictors, our model does not have any control variables. All independent variables are based on the variables used by Palepu (1986), otherwise deviations are clearly stated. Our source for financial information when calculating the variables for targets and non-targets is Thomson Reuters Eikon and the currency is SEK. Note that the observation year for targets and non-targets in the estimation sample is the year they are distributed according to Table 2 while all firms in the hold-out sample have 2015 as the observation year.

Table 3.
Summary of the variables

Hypothesis	Variable	Expected sign
Price-earnings	PE	-
Market-to-book	MTB	-
Inefficient management	AER	-
Size	SIZE	-
Industry disturbance	IDUMMY	+
Growth-resource-mismatch[3]	GRDUMMY LEVERAGE LIQIUDITY GROWTH	+
Institutional shareholding	NETCHG	-
Tangible fixed assets	REALPROP	+

P/e-ratio (PE): To test the price-earnings hypothesis, a p/e-ratio will be used. The p/e-ratio is calculated using the price of the stock (item "Price Close" in Thomson Reuters Eikon) at the end of the last financial year prior to the year of the observation multiplied by the common shares outstanding (item "Total Common Shares Outstanding" in Thomson Reuters Eikon) at the end of the last financial year prior to the year of the observation and the sum is then divided by net earnings (item "Net Income After Taxes" in Thomson Reuters Eikon) for the financial year prior to the year of the observation.

[3] *Note that LEVERAGE, LIQUIDITY and GROWTH carry no expected signs since they are mainly used to calculate the variable GRDUMMY. They will however be included in Palepu Model 2 and the Thesis Model, but following the methodology of Palepu (1986), no expected sign will be assigned to the variables.*

Market-to-book ratio (MTB): The market-to-book hypothesis will be estimated by a market-to-book ratio. The variable is defined as the common shares outstanding at the end of the last financial year prior to the year of the observation (item “Total Common Shares Outstanding” in Thomson Reuters Eikon) multiplied with the price of the stock (“Price Close” in Thomson Reuters Eikon) at the end of the financial year prior to the year of the observation. The sum represents the market value of equity, which is then divided by the book value of equity (item “Total Equity” in Thomson Reuters Eikon) at the end of the financial year prior to the year of the observation.

Size (SIZE): To test the size hypothesis, firm size will be measured using the net book value of the assets (item “Total Assets, Reported” in Thomson Reuters Eikon) of the firm at the end of the financial year prior to the year of the observation. The variable is in billions SEK.

Average excess return (AER): The hypothesis inefficient management is measured as the excess return on a firm’s stock. Palepu (1986) tried in his third and fourth model to substitute AER for ROE but found it not be significant and with an opposite value of the coefficient than what the hypothesis suggests. We will therefore exclude ROE from our model. AER will be measured as the average daily stock return for the four years prior to the year of the observation. However, given the limited data on historical beta values of Swedish firms in Thomson Reuters, the OMX Stockholm All-Share Index (item “OMX STOCKHOLM OMXS” in Thomson Reuters Eikon) will be used as the market portfolio to which we compare the stock’s performance against, instead of a required rate of return using the capital asset pricing model (CAPM) as in Palepu (1986). The daily performance of the index will be deducted from the daily stock return and the average of the four-year daily difference of each stock is used as the variable AER.

Industry dummy (IDUMMY): To capture the industry disturbance hypothesis, an industry dummy variable will be used. However, unlike the definition of the variable used by Palepu (1986): "the variable (IDUMMY) is assigned a value of one if at least one acquisition has occurred in a firm's four digit SIC industry during the year prior to the year of the observation", the dummy variable used in this thesis is the same variable used by Cudd and Duggal (2000): "and is instead capturing acquisitions in the industry of the firm the 12 months after the month of the acquisition". Cudd and Duggal (2000) found that the change in the definition of the variable lead to the variable becoming significant and with a sign consistent with the hypothesis.

Leverage (LEVERAGE): Leverage is measured using the average ratio of book value of debt (item "Total Debt" in Thomson Reuters Eikon) to the book value of equity (item "Total Equity" in Thomson Reuters Eikon) for the three financial years preceding the year of the observation.

Liquidity (LIQUIDITY): Liquidity is measured using the average ratio of net liquid assets (item "Cash and Short Term Investments" in Thomson Reuters Eikon) less current liabilities (item "Total Current Liabilities" in Thomson Reuters Eikon) to the book value of total assets (item "Total Assets, Reported" in Thomson Reuters Eikon) for the three financial years preceding the year of the observation.

Growth (GROWTH): Growth is measured as the compounded average growth rate for sales (item "Net Sales" in Thomson Reuters Eikon) at the end of the financial year prior to the year of the observation and sales at the end of the financial year three years prior to the year of the observation.

Growth-resource dummy (GRDUMMY): To measure the growth-resource-mismatch hypothesis we will use a dummy variable that is assigned the value of one if a firm has low growth, high liquidity and low leverage or high growth, low liquidity and high leverage and zero otherwise. High liquidity, leverage and growth is measured based on the population average of the three financial years preceding the year of the observation, where high is a value above the average and low any other value.

Net change in institutional shareholding (NETCHG): The institutional shareholding hypothesis will be measured using the net change in institutional shareholding. The variable NETCHG is defined as the net change in institutional shareholding[4] (item "Bank and Trust", "Investment Advisor", "Hedge Fund", "Pension Fund" & "Insurance Company" in Thomson Reuters Eikon) of the quarter prior to the date of the observation. Data is collected from Thomson Reuters Eikon Shareholder History Report for each of the sample firms.

Tangible assets-to-total assets (REALPROP): To measure the tangible fixed assets hypothesis, the tangible assets-to-total assets ratio will be used. The variable is based on the net value of property, plant and equipment (item "Property/Plant/Equipment, Total – Net" in Thomson

[4] *Institutional investors are entities such as bank trusts, insurance companies, mutual funds, and pension funds that invest funds on the behalf of others (Bushee, 1998).*

Reuters Eikon) to total assets (item "Total Assets, Reported" in Thomson Reuters Eikon) at the end of the financial year prior to the year of the observation.

4.3.3. Dependent variable

Our dependent variable (Y) is a binary variable: either the firm is a target (Y=1) with the probability ρ or it is not a target (Y=0) with the probability $1-\rho$, no other outcome exists, i.e. the variable is mutually exclusive.

4.4. The prediction test

4.4.1. The prediction model

The logistic probability model used by Palepu (1986) will be the base for our probability estimations of a particular firm being classified as a target and thus the same model will be employed in our study as well. Unlike the result from using a linear regression model, using the logistic regression model will give us a probability of a firm being a target between one and zero. Our logit probability model is:

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

The variables in the model have the following explanations: $\rho(i,t)$ is the probability that firm i will be subject to a takeover bid in the time period t, $x(i,t)$ is a vector of our own selected financial measures of the firm and industry attributes and β is a vector of unknown parameters that will be estimated. The model is tested on the hold-out sample and the regression model with the highest explanatory power will be used as the prediction model.

4.4.2. Cutoff probability

The cutoff probability is used in order to test the prediction rate of the estimated regression model. It is used by comparing the cutoff probability with the estimated probability of a particular firm being a target. If the probability is equal to or higher than the cutoff probability, the firm is classified as a target and if the probability is lower, the firm is classified as a non-target. Two methods are used to determine the cutoff probability. One method, commonly used in state-based sampling methods, is to use an arbitrary chosen cutoff probability of usually 0.5 (see, e.g. Simkowitz & Monroe, 1971; Stevens, 1973; Powell, 2001). This is because the sampling method assumes an equal distribution of targets and non-targets in the population. It results in an overstated prediction rate and when tested on the entire population, it generates high classification errors, i.e. type I and type II errors (Palepu 1986). It is a consequence of the true distribution of targets and non-targets in the population being weighted towards non-targets and the cutoff probability must therefore be adjusted for this fact (Palepu, 1986). Palepu (1986) argued it is important because the cutoff probability should be based on the intended use of the model, i.e. the entire population of firms.

Palepu (1986) therefore proposed an alternative method for estimating the cutoff probability that he argued provided fairer prediction rates and led to a lower number of misclassification errors. After Palepu (1986) used the method, he received a cutoff probability of 0.112, much lower than the commonly used probability of 0.5. In addition, Cudd and Duggal (2000) employed the same method and received cutoff probabilities for their three models of 0.128, 0.136 and 0.158. Based on the above reasoning, we will follow the same methodology as Palepu (1986) and thus calculate our optimal cutoff probability since our intended use of the model is to employ it on the entire population.

The method suggests that the optimal cutoff probability is calculated using the acquisition probability distributions, generated from the prediction model, of non-targets and targets of the estimation sample. The result can empirically be generated by plotting the results from the probability distributions of targets and non-targets in the same graph. It is accomplished by dividing the range between the lowest and the highest estimated probability of all the firms (targets and non-targets) into equally big intervals and then to distribute each group of firms into these intervals based on their estimated probabilities to create one distribution for targets and one for non-targets. The number of intervals is chosen arbitrarily, Palepu (1986) for instance uses ten and since no explanation is given for how to choose an optimal number, we will use the same number. The point where the two lines cross is the optimal cutoff probability. To illustrate, consider a firm that has an estimated acquisition probability equal to the probability where the two distributions meet. The probability of this firm being an actual target is equal to the probability of the same firm being an actual non-target as this is the point where the distribution of targets and non-targets is equal. Following the same logic, all firms with estimated acquisition probabilities greater than the point where the two distributions intersect are expected to be targets.

5. Results

This section will first give a presentation of the descriptive statistics for the variables in our regression models. A test for Pearson correlations will then be made to test for correlation between the independent variables and after that, the results of the regression models are presented. Lastly, we present the results of our robustness tests, including tests for multicollinearity, differences in sampling methods, results from changing the definition of the SIZE variable and differences between unadjusted and industry-adjusted variables.

5.1. Descriptive statistics

Differences in mean and median value of all unadjusted variables used are presented in Table 4. The reason why we include unadjusted variables and not industry-adjusted variables is because the unadjusted variables are more intuitive. To exemplify, the mean value for the industry-adjusted PE variables for the entire sample is zero, which tell us nothing about the actual levels of p/e-ratios in the samples. Therefore, we are mainly interested in observing the t-tests for differences in mean values for the industry-adjusted variables, hence included in the row to the far right in Table 4. However, a complete presentation of the descriptive statistics for adjusted variables is found in Appendix 8.

The t-tests for the unadjusted variables show that only SIZE and NETCHG have significant differences in mean values between the subsamples targets and non-targets. SIZE is significant at the 10% level and NETCHG at the 5% level. The interpretation is that target firms are smaller in size than the non-target firms during the period 2005-2014. Palepu (1986) found similar results in his study. Likewise, the change in institutional shareholding the quarter before the announcement of the bid is larger for targets compared to non-targets. This is in contrary to the findings of Ambrose and Megginson (1992) that supported the opposite. In addition, neither the inefficiency nor the undervaluation variables (ARE, MTB and PE) are significant. The same results hold for t-tests for industry-adjusted variables with the exception of SIZE and NETCHG. Differences in mean values for SIZE are significant at the 10% level and insignificant for NETCHG for the industry-adjusted variables.

Table 4.
Descriptive statistics

Variable	Target subsample (n=76) Mean value	Target subsample (n=76) Median value	Non-target subsample (n=110) Mean value	Non-target subsample (n=110) Median value	t-Test for difference in mean values[5]	t-Test for difference in mean values[6]
PE[7]	9.851	12.060	9.948	11.858	0.016	0.201
MTB	2.492	2.026	2.666	2.091	0.471	0.499
GROWTH	0.129	0.056	0.117	0.068	-0.260	-0.641
LEVERAGE	0.849	0.256	0.597	0.494	-0.936	-0.865
LIQUIDITY	-0.198	-0.193	-0.159	-0.192	1.129	1.196
GRDUMMY	0.237	0.000	0.264	0.000	0.411	0.411
AER	0.001	0.001	0.002	0.001	1.054	0.653
SIZE	4.010	0.892	12.500	1.690	1.942*	2.223**
IDUMMY	0.684	1.000	0.582	1.000	-1.417	-1.417
NETCHG	0.036	0.001	0.001	0.001	-2.527**	-1.455
REALPROP	0.177	0.042	0.183	0.098	0.177	0.073

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

5.2. Pearson correlations

Pearson correlations are presented in Appendix 9 in order to recognize significant correlations between the independent variables. The test will help raise awareness of potential problems with multicollinearity in the data and if further tests should be conducted. In general, our variables have very low correlations. A few have statistically significant correlations, but with low coefficients. LEVERAGE has the highest correlations, significant at the 1% level with MTB, LIQUIDITY and REALPROP. REALPROP and AER also have relatively high correlations, with AER being significant at the 1% level with GROWTH and MTB and REALPROP at the 1% level with GROWTH and at the 5% level with SIZE and MTB. Further test for multicollinearity will be made as a robustness test after the regression model have been estimated in order to be certain that these correlations do not affect the results.

[5] *t-Test for differences in mean values between unadjusted variables.*
[6] *t-Test for differences in mean values between industry-adjusted variables.*
[7] *Newbold, Carlsson and Thorne (2012) suggests that an extreme observation is defined as the sum of the mean and two standard deviations. When applying this method one extreme PE observation is discovered and deducted from the sample. After this adjustment the mean value of the PE for the Target Subsample decreased from 49 to approximately 10. We therefore believe it is sufficient to remove the observation.*

5.3. Results from the regression models

The coefficient estimates of each model are presented in Table 5. The estimates are in log-odds units which differ in interpretation from a linear ordinary least squares (OLS) regression. The coefficient for MTB can for instance be interpreted as an increase in one unit of the independent variable MTB is expected to lead to a change of -0.057 in the log-odds of the dependent variable, holding the other independent variables constant. McFadden's pseudo R^2, in Table 5 presented as the likelihood ratio index, is according to Wooldridge (2015) similar to the R^2 statistic used in linear OLS regressions and reflects the goodness-of-fit of the model. However, the R^2 statistic for linear OLS regressions is in general higher than pseudo R^2. A value higher than 0.2 for pseudo R^2 is considered a good explanatory power according to Hensher and Stopher (1979). The related likelihood ratio statistic is a test of the statistical significance of the explanatory power of the model.

Table 5.
Regression output matched adjusted sample

Variable	Expected sign	Palepu Model 1 Coef.	Palepu Model 1 z-Stat	Palepu Model 2 Coef.	Palepu Model 2 z-Stat	Thesis Model Coef.	Thesis Model z-Stat
PE	-	-0.00001	-0.001	-0.012	-0.070	-0.001	-0.001
MTB	-	-0.057	-0.330	-0.059	-0.330	-0.072	-0.390
GROWTH				0.109	0.650	0.055	0.310
LEVERAGE				0.112	0.650	0.115	0.580
LIQUIDITY				-0.175	-0.950	-0.138	-0.730
GRDUMMY	+	-0.126	-0.330	-0.001	-0.001	-0.090	-0.220
AER	-	-0.105	-0.600	-0.116	-0.650	-0.118	-0.660
SIZE	-	-0.568**	-2.070	-0.598**	-2.090	-0.604**	-2.090
IDUMMY	+	0.627*	1.810	0.568	1.630	0.582*	1.660
NETCHG	-					0.186	1.090
REALPROP	+					-0.057	-0.300
Constant		-0.796	-1.250	-0.684	-1.050	-0.676	-1.020
Year Fixed Effects[8]		-		-		-	
No. of observations		186		186		186	
No. of targets		76		76		76	
Likelihood ratio index		0.0429		0.0514		0.0568	
Likelihood ratio statistic		10.790		12.930		14.290	

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

[8] *Year fixed effects are included in all of the three models as stated in section 4. However, we will only show whether the effects are significant or not. Significance will be indicated using "*" as for the other variables.*

The results from Palepu Model 1 show that SIZE and IDUMMY are significant at the 5% level and the 10% level respectively. SIZE and IDUMMY also carry the same signs as expected by their hypotheses, with SIZE being consistent with the results of Palepu (1986). The results imply that smaller firms are more likely to become takeover targets in a Swedish setting between 2005 and 2014. IDUMMY have however results not in line with the results of Palepu (1986), who found the variable significant at the 10% level and with an opposite sign as proposed by the industry disturbance hypothesis. This implies that firms in industries with recent acquisition activity are more probable to become takeover targets in a Swedish setting, while the opposite is true for American firms in the 1970s. Moreover, neither AER nor GRDUMMY are significant in our study, which they are in Palepu (1986). PE and MTB are also insignificant. Palepu (1986) found the same regarding PE and MTB. It is also notable that year fixed effects are not significant in the model.

When adding LEVERAGE, LIQUIDITY and GROWTH to Palepu Model 2, the results are very similar with only small changes in the coefficients and z-statistics of the variables. An interesting finding is nonetheless that IDUMMY is insignificant. Concerning the added variables, LIQUIDITY has a negative sign and LEVERAGE and GROWTH have positive signs. They are all however insignificant, indicating no significant difference in leverage, liquidity and growth between targets and non-targets. These results are not consistent with Palepu (1986) as LEVERAGE and GROWTH in his models are found to have negative signs and significant z-statistics.

The previous results of Palepu Model 1 and Palepu Model 2 hold in the Thesis Model as well, with only small alterations in the coefficients and significances except for IDUMMY now becoming significant again at the 10% level. Regarding the two added variables NETCHG and REALPROP, the results are different from expected. Unlike the results of Ambrose and Megginson (1992) that indicated NETCHG and REALPROP to be significant variables and carry the same sign as their proposed hypotheses, our model shows the opposite. NETCHG has a positive sign and REALPROP a negative sign and they are both insignificant. Hence, no difference among targets and non-targets in the change of institutional shareholding and the tangible assets to total assets ratio can with certainty be concluded.

Palepu (1986) estimated the likelihood ratio of his most significant model to be 0.1245. The likelihood ratio indexes in this paper are lower than in Palepu (1986), ranging from 0.0429 in

Palepu Model 1 to 0.0568 in the Thesis Model. The three models come with likelihood ratio chi-square values ranging between 10.79-14.29 and associated p-values ranging between 0.7676-0.8156, which tells us that the likelihood ratio indexes for all three models are not statistically significant and does not provide a statistically significant explanation of the acquisition likelihood. However, even though the model's explanatory power is insignificant, the model can still produce significant variables as indicated in Table 5.

5.4. Robustness tests

A number of robustness tests will be presented in the following subsections to verify that the results from the regression models are stable.

5.4.1. Multicollinearity

Following the results of the test for Pearson correlations, an analysis for multicollinearity is made. Multicollinearity refers to a case where the independent variables in a regression model are highly correlated with each other. When variables are highly correlated with each other it can be challenging to interpret the result of a regression since the contribution of an independent variable to the regression is hard to separate (Farrar & Glauber, 1967). The first test is conducted by regressing each independent variable individually against the dependent variable with the results presented in Appendix 1. It is made to ensure that the results of the main regression model, in particular the results of SIZE and IDUMMY, are not a consequence of correlation between independent variables. The only significant variable is SIZE, which is significant at the 5% level. Moreover, no large alterations in the coefficients of the predictors can be seen with the exception of PE, IDUMMY and REALPROP that have z-statistics notably different than in the main regression models. They are still nevertheless insignificant. Since IDUMMY is insignificant when we test it separately against the dependent variable but is significant in two of the main regression models, we cannot rule out the fact that the results in the main regression model for IDUMMY are affected by correlation between the variable and other independent variables. In order to determine the magnitude of the problem, a variance inflation factor (VIF) analysis is conducted as a second test for multicollinearity, with the results tabulated in Appendix 2. In previous literature (Wooldridge, 2015), a VIF of 10 is an indication of excessive or serious multicollinearity. A discussion on the VIF-test is made in section 6.2.

5.4.2. Change in the definition of SIZE

Since SIZE is the variable we find the most significant evidence for, another robustness test is conducted specifically for the variable. The test is made by simply changing the definition of the variable. The new definition is to measure the variable as the market capitalization of the company instead of the total assets[9]. The results from the regression with the new definition being substituted for the previous one is presented in Appendix 3. The z-statistic and the coefficient changes as a result of the change in the definition. The variable SIZE is still nevertheless significant, but at the 10% level, and the coefficient carries the same sign as with the previous definition. Noteworthy is that the IDUMMY is no longer significant in any of the models and that the overall explanatory power of the models drop.

5.4.3. Differences in sampling methods

Since we use a different sampling method than Palepu (1986), a robustness test is made in order to determine the effects of the change in sampling method. The results of the main regression models based on the method of Palepu (1986) are presented in Appendix 4. The differences in the results are noticeable. The regression models based on the sampling method used by Palepu (1986) are all statistically significant and have likelihood ratio indexes of 0.1870, 0.1930 and 0.2056. MTB, AER and SIZE are significant at the 5% level in all three models and IDUMMY is significant at the 1% level in all three models. NECTHG is also significant, but at the 10% level. However, the SIZE variable carries the same sign and is significant at the 5% level regardless of sampling method. In addition, PE, LEVERAGE, LIQUIDITY, GROWTH, GRDUMMY and REALPROP also have similar results from both sampling methods as they are all insignificant irrespective of sampling method used.

5.4.4. Adjusted vs unadjusted variables

A last robustness test is conducted in order to review the effects of using industry-adjusted variables instead of unadjusted variables. The results of running the same regression models are presented in Appendix 5. The explanatory power of the unadjusted models range from 0.0523 to 0.0901. Hence, the explanatory power of the unadjusted models are higher than the explanatory power of the industry-adjusted models, which is inconsistent with the result of

[9] *The market capitalization is calculated using information from Thomson Reuters and is defined as the closing stock price (item "Price Close" in Thomson Reuters Eikon) multiplied by the number of shares outstanding (item "Total Common Shares Outstanding" in Thomson Reuters Eikon). The variable is still measured in billions SEK as before and the information date is unchanged.*

Cudd and Duggal (2000) that found the opposite to be true. Yet, none of the models are significant. The results of the specific variables also differ. IDUMMY is significant at the 10% level in Palepu Model 1. Furthermore, SIZE drops in significance from the unadjusted model and is now only significant at the 10% level for all three models. NETCHG is similarly significant but at the 5% level. As in previous regression models, PE, LEVERAGE, LIQUIDITY, GROWTH, GRDUMMY and REALPROP remain insignificant.

5.5. Prediction test

5.5.1. Optimal cutoff probability

Before being able to test the estimated models with a prediction test, the optimal cutoff probability must be calculated. The estimated acquisition probabilities range from 0.008 to 0.737. All acquisitions probabilities are within the range 0-0.75 and this range is divided into ten equally big intervals. The distribution of all firms according to these intervals is presented in Appendix 10 and the plotted graph of the probability distributions for non-targets and targets is presented in Appendix 6. In Appendix 6, the y-axis represents the percentage of firms from both distributions in each interval and the x-axis simply denotes each interval. The two distributions intersect at the point 0.493, which is the optimal cutoff probability for the given sample.

5.5.2. The prediction model

The estimations are based on the coefficients from the regression model with the highest explanatory power, hence the Thesis Model. After comparing the estimated acquisition probabilities to the optimal cutoff probability, the following results are obtained. Four out of 11 actual targets are correctly classified as targets, equaling a prediction rate of 36%, i.e. four actual targets have an estimated acquisition probability higher than the cutoff probability of 0.493. The results are inferior to Palepu (1986) who achieved a prediction rate for targets of 80%. In addition, it implies that the prediction error rate for targets, the fraction of actual targets classified as non-targets, is 64%. For non-targets, 71 out of 110 are classified correctly which indicates a prediction rate of 65% and a prediction error rate of 35%. The predication rate for non-targets is on the other hand much higher than for Palepu (1986) who predicted 45% of the non-targets correctly. The total weighted prediction rate of the model is subsequently calculated to 62%.

6. Discussion

In this section we will discuss our results and connect them to the stated hypotheses. The first discussion will be concentrated on understanding the results from the descriptive statistics and the regression models. This will be followed by a discussion about the numerous robustness tests that have been made. Lastly, a discussion of our prediction model and the prediction rate of the model will be conducted.

6.1. Analysis of results

The overall results are disappointing as we only find support for two of our hypotheses. The variable SIZE is significant across all three models, with z-statistics ranging from -2.070 in Palepu Model 1 to -2.090 in the Thesis Model. Therefore, we can at the 5% level with statistical significance conclude that the firm size hypothesis hold as our findings support that in a Swedish setting the probability of a smaller firm becoming a takeover target is higher than the probability of a larger firm. The result is interesting, especially considering the similar results of previous studies in an American setting (Hasbrouck, 1985; Palepu, 1986; Ambrose & Megginson, 1992; Cudd & Duggal, 2000) and in a British setting (Powell, 1997).

Moreover, the results from the regression model of IDUMMY are somewhat puzzling. When adding the variables LEVERAGE, LIQUIDITY and GROWTH to Palepu Model 2, the IDUMMY goes from being significant at the 10% level to being insignificant and when NETCHG and REALPROP are added to the Thesis Model, the variable becomes significant at the 10% level again. This is particularly surprising considering that IDUMMY is shown to have no significant Pearson correlations with the other independent variables. What should be mentioned is however that the changes in the z-statistics and the coefficients are relatively small, making the variance hard to interpret. We can still find evidence with statistical significance at the 10% level in two of our models that Swedish listed firms in industries with previous M&A activity during the last 12 months are more likely to become takeover targets than firms in industries with no previous M&A activity. The results are consistent with the early research on the industry disturbance theory of Gort (1969) and the takeover prediction study of Cudd and Duggal (1992) in an American setting. Palepu (1986) on the other hand found the IDUMMY variable to also be significant, but with an opposite sign.

We find no support for the rest of the six hypotheses and can therefore not reject their null hypotheses, implying that undervaluation and inefficiency linked variables are not useful for predicting takeover targets in a Swedish setting. There seem instead to be other reasons for acquiring firms during the examined period. The results are inconsistent with the findings of Hillström and Jacobsson (1998) who find p/e-ratios to be an important factor in predicting Swedish takeover targets. This is an interesting result, building on the research of Powell (1997) who found that takeover prediction models are not stable over time. Additionally, institutional shareholding and tangible assets do not seem to be indicators of takeover vulnerability. The fact that very few hypotheses are supported is also reflected in the likelihood ratio indexes of the models ranging from 0.0429 to 0.0568, which are significantly lower than for Palepu (1986) since his highest estimated index was 0.1245. Palepu (1986) likewise found all of his three models to be significant, while we find none of our models to be. This is of course a great limitation of the models in this study and very little can accordingly be concluded about their predictive ability and usefulness. One explanation for these results is the use of an alternative sampling method than Palepu (1986). When comparing the results of using the same sampling method, the likelihood ratio index levels exceed the levels achieved by Palepu (1986). It is obvious that the choice of sampling method has a clear impact on the estimations of the regression model. We will further elaborate on the effects of our choice of sampling method in section 6.2. The fact that we estimate our model on a different setting and in a different period of time is of course also likely to have an impact.

In regard to the descriptive statistics in Table 4, it is clear that the industrial adjustment of the variables has had an effect on the estimated model given that NETCHG has a significant difference in mean values at the 5% level between targets and non-targets for unadjusted variables but insignificant difference when doing the same test with adjusted variables. It is therefore likely that the average level of change in institutional shareholding differs among industries and that these differences are bigger than the difference among targets and non-targets. This supports our choice of choosing to industry-adjust our independent variables in order to be able to include firms from all industries in our sample. It is also notable that the z-statistic of SIZE increases when we industry-adjust the variable. The same results are observed when the regression models are estimated using both adjusted and unadjusted variables. This indicates that smaller firms are not just more likely to become takeover targets because they belong to industries in which firms on average are smaller but that the finding of smaller firms having higher takeover likelihoods holds across industries.

6.2. Robustness tests

The results from our VIF calculations prove that our data does not contain problematic levels of multicollinearity as none of our variables have VIF values above 4. Therefore, we can rule out that our interpretations and conclusions are significantly affected by correlations between independent variables. This is particularly interesting for the interpretation of SIZE and IDUMMY given that they are the only significant variables in our Thesis Model. We can consequently rely on their contribution to the regression model. Moreover, when we test each variable separately against our dependent variable it is notable that SIZE is the only significant variable. This implies that the results of the main regression model for SIZE are not an effect of correlation to other independent variables, but that smaller firms in fact are more likely to be takeover targets in a Swedish setting than larger firms.

The other variable that is interesting to interpret is IDUMMY because of it being significant in two of our regression models. Yet, when regressing IDUMMY alone against the dependent variable, it is not significant. The finding is surprising since IDUMMY does not have significant Pearson correlations with any other independent variable. However, when we test the multicollinearity of each variable with a VIF analysis we find that IDUMMY receives the largest VIF of all variables, yet far from the range of problematic levels of multicollinearity. There seem to instead be other reasons to why IDUMMY is not significant on a stand-alone basis when regressed against the dependent variable. Consequently, it is hard to interpret why IDUMMY is significant in two of the regression models and at the same time not significant when testing the variable separately against the dependent variable. As a result, it is difficult to be conclusive about IDUMMY and its contribution to the models.

Another proof of the importance of firm size as a characteristic of takeover targets is the test presented in section 5.4.2. The results from the regression with another definition of size shows that the variable is still significant and that its estimated coefficient carries the same sign as before. However, the variable is after the change only significant at the 10%, indicating a drop in its contribution to the model. We interpret it as a weakness of the size hypothesis as the result is an indication that the hypothesis is sensitive to the definition of the related variable. As a consequence, we become less conclusive about the hypothesis. Building on the discussion on IDUMMY in the paragraph above, we see that IDUMMY becomes insignificant in all three models when changing the definition of the variable SIZE. This could be an effect of IDUMMY being a function of the other independent variables, and given that SIZE is found to be the only significant variable other than IDUMMY in the regression models, IDUMMY could be a function of SIZE. To illustrate, IDUMMY is dependent on previous M&A activity in the industry. Hence, we would expect industries where there is a higher number of smaller firms to have high M&A activity given that SIZE is a significant variable. Thus, when the SIZE variable drops in significance, it is logical to believe that the IDUMMY variable should drop in significance as well. The same reasoning could provide an explanation for why IDUMMY has a noteworthy variance in significance in the main regression models.

To see if our results are robust to changes in sampling method, we test our hypotheses using a sample selection based on Palepu (1986). The suggested conclusion based on the results is that the sampling method of Palepu (1986) provides better estimations of the variables than a matching scheme sampling, resulting in a higher explanatory power of the model. However, using the sampling method based on Palepu does not take into consideration effects of yearly trends on financial variables since the data for non-targets is collected during the last year of the studied period. The reason for using our sampling method was to account for temporal differences as we believed the selected time-period was rather unstable in terms of economic cycles compared to the period examined by Palepu (1986). Our decision mainly relies on the research of Barnes (1990) and Powell (2001) who both argued that the prediction model should hold over time. In addition, Barnes (1990) in particular pointed out that macroeconomic factors affect the temporal stability of prediction models. Given that the results of time-fixed effects are insignificant in the main regression models, we managed to at least ease these temporal effects.

Moreover, the result from industry-adjusting the independent variables were different from what we would have expected. The explanatory power of the model decreased, while Cudd and Duggal (2000) managed to increase the explanatory power using the same method. However, as the models are insignificant, little can be concluded about whether the unadjusted or the adjusted variables provide a better model. Still, we hypothesise the limited sample to be an explanation for why the explanatory power is higher for the unadjusted model. Barnes (1999) pointed out the importance of having a sufficient representation of firms in every industry in order to be able to industry-adjust variables. This is a major problem in our data considering that the sample consists of a low number of firms across ten different industries. Cudd and Duggal (2000) on the other hand only used firms from two industries. More infrequent industries, like utilities and telecommunication services only consists of two and three firms respectively in our sample. Estimating standard deviations and averages on samples this small is likely to result in values not representable for the entire industry. It is therefore possible that our industry-adjusted variables may suffer from problems of limited observations. Perhaps a better methodology would have been to use industry fixed effects. However, since very little previous research in this area has used industry fixed effects, we felt reluctant to employ them and instead decided to follow the more commonly used methodology of industry-adjusted variables.

6.3. Prediction model

To calculate acquisition probabilities, the Thesis Model has been used since it has the highest likelihood ratio index. However, it is important to emphasize that this model is insignificant and therefore we would not expect its predictive ability to be accurate. Having an insignificant estimation model when calculating predicted values comes with limitations, since it could be difficult to interpret results and draw conclusions from such a model. Indeed, the results from the prediction tests are in line with this guess. The number of type I errors is 65%, which is substantially higher than the 20% reported by Palepu (1986). What is noteworthy nonetheless is that the number of type II errors is considerably lower in our study than in Palepu's (1986), 35% compared to 55%. This is a weakness of our model, since the goal itself is to predict as many targets as possible and if the goal of the model is to generate an abnormal return, the cost of type I errors is greater than the cost of type II errors. To illustrate the low usefulness of the prediction model, if one were to randomly pick 43 firms (the number of firms our model predicts as targets) out of our hold-out sample, one is expected to pick 4.3 targets[10]. Our models correctly predicts four targets. Hence, the model is not better than chance in predicting takeover targets as indicated by its insignificant explanatory power. The results therefore do not indicate that IFRS has had a positive impact on the prediction rate of takeover prediction models nor that the accounting quality of Sweden increases the predictive ability of these models.

We hypothesise that these results could stem from the use of a high cutoff probability. It is likely that it is a result of the fact that our estimated model is insignificant. It is therefore not possible to rely on the estimated acquisition probabilities it generates, potentially leading to a skewed cutoff probability. Both Palepu (1986) and Cudd and Duggal (2000) calculate their optimal cutoff probabilities using statistically significant models and receive much lower values

[10] *43 times the fraction of targets in the hold-out sample (11/121) is equal to 4.3.*

between 0.1 and 0.15, compared to ours of 0.493. Our cutoff probability more resembles the arbitrary cutoff probabilities of around 0.5 used in Powell (2001) and other studies using the state-based sampling method. It is logical to believe that a higher cutoff probability will result in fewer actual non-targets being classified as targets but also fewer actual targets being classified as a target. Powell (2001) for instance receives very similar results as we do, with higher type I errors but lower type II errors compared to Palepu (1986).

7. Conclusion

This study first examines characteristics of takeover targets of Swedish listed firms and second tests the possibility of constructing a statistical model to predict future takeover targets on the Swedish stock market. Limited supporting evidence is found for most of our hypotheses, indicating that Swedish takeover targets and non-targets are more homogenous than expected. Yet, consistent with previous studies in an American and British setting, smaller firms, in terms of total assets, are indicated to be a significant characteristic of Swedish takeover targets. The results are significant at the 5% level and hold for several robustness tests. In addition, more suggestive support is found for firms having higher takeover probabilities if they belong to industries with previous M&A activity. These findings are however only significant at the 10% level and do not hold for robustness tests. We are therefore less conclusive regarding this characteristic.

The overall results of the predictive ability of the model offer little support for the possibility of creating a takeover prediction model. Moreover, since none of our models are found to be significant, the study is believed to be of little use. The results of this study suggest that the implementation of IFRS has not improved the ability to construct takeover prediction models. Additionally, using a Swedish setting do not seem to increase the predictive ability of prediction models, rather the opposite is indicated.

8. Limitations

First it should be mentioned that the hypotheses and variables explored in this study in order to predict takeover targets do not represent a complete set of potential variables. There are numerous other variables to investigate that could potentially increase the predictive ability of the model. For instance, a limitation of the variables used in this study is that they are in general based on rather old research conducted on firms in the US and the UK. We cannot therefore conclude that takeover targets are impossible to predict using variables based on public information, but that the results of this study could rather be an effect of an inadequate choice of independent variables.

Moreover, as discussed in section 6.2, the limited number of observations on the Swedish stock market provide a great obstacle for this study. In an attempt to tackle this problem, we include several industries and use industry-adjusted variables, whereas similar studies in more observation-rich settings limit their sample to fewer industries. Due to an insufficient amount of observations across industries, the attempt to compensate the use of multiple industries with industry-adjusted variables is likely to negatively affect the statistical adequacy of the model. The surprising results of the industry-adjusted model in comparison to the unadjusted model are possibly a consequence of this.

9. Directions for future research

During the process of conducting this thesis we have identified several potential interesting directions for future research. First and foremost, limited research regarding takeover prediction on the Swedish market has been conducted. We find that one problem stem from the very small population of firms and we therefore strongly believe that it is of great importance to extend the sample size. It could therefore be wise for future research to include perhaps the Scandinavian market as this would result in a sample consisting of more firms attributable to fewer industries.

Furthermore, this study finds compelling evidence for size being an important takeover target characteristic. Given the similar results of studies in the US and the UK (see, e.g. Palepu, 1986; Powell, 1997; Cudd & Duggal, 2000) an interesting area of research would be to extend the study of Hasbrouck (1985) to explore the reasons to why firms systematically seem to acquire smaller firms.

Lastly, this study is among the first to examine takeover prediction during the period after the implementation of IFRS. Since we find no support for IFRS positively affecting the ability to predict takeover targets, it would be interesting to see the effects of IFRS on other settings, for instance the UK.

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Appendix

Appendix 1.
Test of adjusted variables separately

Variable	Expected sign	Coefficient	z-Stat
PE	-	-0.031	-0.200
MTB	-	-0.078	-0.500
GROWTH		0.094	0.640
LEVERAGE		0.132	0.860
LIQUIDITY		-0.185	-1.190
GRDUMMY	+	-0.143	-0.410
AER	-	-0.101	-0.650
SIZE	-	-0.521**	-2.010
IDUMMY	+	0.443	1.410
NETCHG	-	0.225	1.430
REALPROP	+	-0.011	-0.070
Year Fixed Effects		-	
No. of observations		186	
No. of targets		76	

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

Appendix 2.
VIF-analysis

Variable	VIF
PE	1.120
MTB	1.300
GROWTH	1.270
LEVERAGE	1.490
LIQUIDITY	1.360
GRDUMMY	1.730
AER	1.250
SIZE	1.050
IDUMMY	2.510
NETCHG	1.130
REALPROP	1.350
Mean year	1.260
Mean total	1.350
No. of observations	186
No. of targets	76

Appendix 3.

Robustness check – Changed definition of SIZE

Variable	Expected sign	Palepu Model 1 Coef.	Palepu Model 1 z-Stat	Palepu Model 2 Coef.	Palepu Model 2 z-Stat	Thesis Model Coef.	Thesis Model z-Stat
PE	-	0.007	0.040	-0.006	-0.040	0.002	0.010
MTB	-	-0.018	-0.110	-0.013	-0.070	-0.023	-0.140
GROWTH				0.116	-0.710	0.066	0.380
LEVERAGE				0.100	0.590	0.102	0.540
LIQUIDITY				-0.150	-0.840	-0.113	-0.610
GRDUMMY	+	-0.035	-0.630	0.091	0.240	0.004	0.010
AER	-	-0.054	-0.330	-0.065	-0.390	-0.069	-0.410
SIZE	-	-0.480*	-1.850	-0.484*	-1.810	-0.476*	-1.770
IDUMMY	+	0.479	1.490	0.439	1.360	0.456	1.400
NETCHG	-					0.177	1.060
REALPROP	+					-0.057	-0.320
Constant		-0.698**	-2.470	-0.709**	-2.500	-0.699**	-2.460
Year Fixed Effects		-		-		-	
No. of observations		186		186		186	
No. of targets		76		76		76	
Likelihood ratio index		0.0309		0.0382		0.0433	
Likelihood ratio statistic		7.790		9.620		10.890	

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

Appendix 4.

Robustness check – Regression with another sampling method[11]

Variable	Expected sign	Palepu Model 1 Coef.	Palepu Model 1 z-Stat	Palepu Model 2 Coef.	Palepu Model 2 z-Stat	Thesis Model Coef.	Thesis Model z-Stat
PE	-	-0.055	-0.300	-0.038	-0.210	-0.042	-0.220
MTB	-	-0.511**	-2.410	-0.550**	-2.480	-0.564**	-2.450
GROWTH				-0.032	-0.170	-0.118	-0.610
LEVERAGE				0.174	0.860	0.149	0.670
LIQUIDITY				0.088	0.440	0.171	0.830
GRDUMMY	+	-0.255	-0.630	-0.286	-0.660	-0.490	-1.080
AER	-	0.435**	2.180	0.445**	2.220	0.432**	2.110
SIZE	-	-0.628**	-2.220	-0.670**	-2.250	-0.621**	-2.140
IDUMMY	+	-1.941***	-5.410	-1.915***	-5.250	-1.917***	-5.190
NETCHG	-					0.383*	1.880
REALPROP	+					0.013	0.070
Constant		0.497*	1.950	0.477*	1.800	0.533**	1.970
No. of observations		186		186		186	
No. of targets		76		76		76	
Likelihood ratio index		0.1870		0.1903		0.2056	
Likelihood ratio statistic		47.070		47.880		51.740	

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

[11] *Year fixed effects are not possible to include given the sampling method since all targets are distributed across 2005-2014 and all non-targets are based in 2015. We understand that changing two factors in the regression model affect its comparability with the main regression models. However, we see no other way to get around this problem and think that it is of high interest to still show the results from changing sampling method.*

Appendix 5.

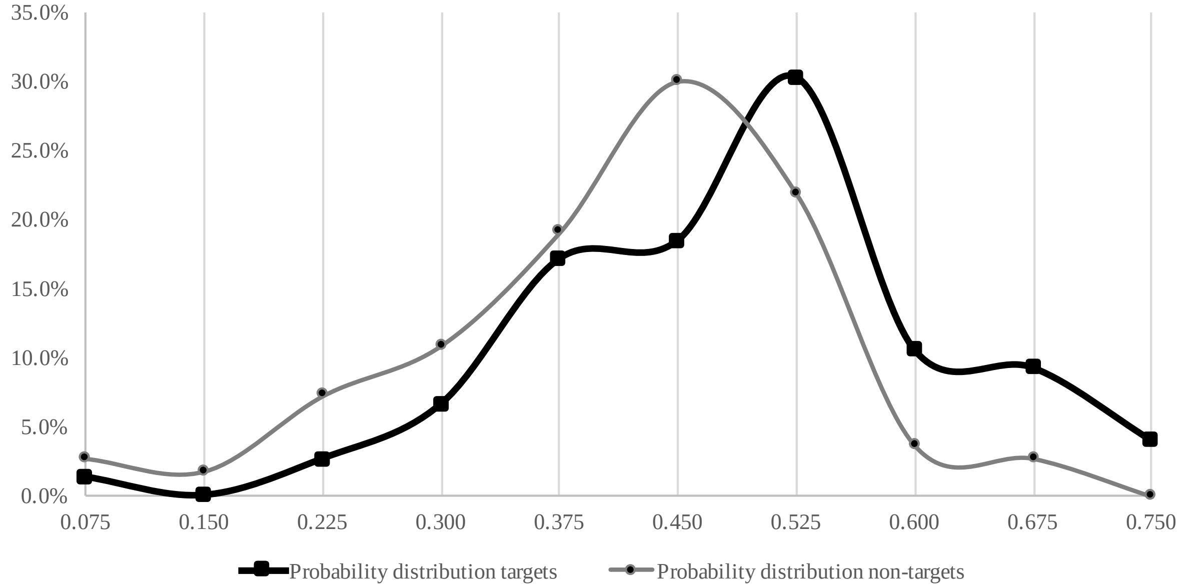
Robustness check – Regression with unadjusted variables

		Palepu Model 1		Palepu Model 2		Thesis Model	
Variable	Expected sign	Coef.	z-Stat	Coef.	z-Stat	Coef.	z-Stat
PE	-	0.0004	0.110	0.0003	0.080	0.0004	0.100
MTB	-	-0.017	-0.240	-0.041	-0.540	-0.037	0.480
GROWTH				0.245	0.440	-0.115	0.190
LEVERAGE				0.128	0.880	0.114	0.790
LIQUIDITY				-0.426	-0.550	-0.132	0.170
GRDUMMY	+	-0.300	-0.770	-0.189	0.460	-0.295	-0.690
AER	-	-44.470	-1.270	-45.900	-1.260	-42.600	-1.150
SIZE	-	-0.000*	-1.880	-0.000*	-1.900	-0.000*	-1.930
IDUMMY	+	0.612*	1.750	0.564	1.550	0.580	1.530
NETCHG	-					7.086**	2.140
REALPROP	+					0.146	0.190
Constant		0.497*	-0.480	0.477*	-0.530	0.533**	-0.550
Year Fixed Effects		-		-		-	
No. of observations		186		186		186	
No. of targets		76		76		76	
Likelihood ratio index		0.0523		0.0598		0.0901	
Likelihood ratio statistic		13.050		14.950		22.510	

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

Appendix 6.

Visualisation of cuttoff probability estimation



Appendix 7.
Distribution of the estimation sample by industry

Industry	Targets	Non-targets	Total
	Number of firms		
Consumer Discretionary	14	18	32
Consumer Staples	2	3	5
Energy	2	1	3
Health Care	9	11	20
Industrials	10	34	44
Information Technology	27	27	54
Materials	6	6	12
Real Estate	3	8	11
Telecommunication Services	2	1	3
Utilities	1	1	2
Total	**76**	**110**	**186**

Appendix 8.
Descriptive statistics industry adjusted variables

	Target subsample (n=76)		Non-target subsample (n=110)		
Variable	Mean value	Median value	Mean value	Median value	t-Test for difference in mean values
PE[12]	-0.020	0.043	0.010	0.045	0.201
MTB	-0.043	-0.243	0.030	-0.205	0.499
GROWTH	0.055	-0.159	-0.038	-0.115	-0.641
LEVERAGE	0.074	-0.320	-0.051	-0.265	-0.865
LIQUIDITY	-0.103	-0.070	0.071	0.047	1.196
GRDUMMY	0.237	0.000	0.264	0.000	0.411
AER	-0.056	-0.101	0.039	-0.005	0.653
SIZE	-0.190	-0.273	0.131	-0.166	2.223**
IDUMMY	0.684	1.000	0.582	1.000	-1.417
NETCHG	0.125	-0.127	-0.086	-0.115	-1.455
REALPROP	-0.006	-0.262	0.004	-0.241	0.073

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

[12] *Newbold, Carlsson and Thorne (2012) suggests that an extreme observation is defined as the sum of the mean and two standard deviations. When applying this method one extreme PE observation is discovered and deducted from the sample. After this adjustment the mean value of the PE for the Target Subsample decreased from 49 to approximately 10. We therefore believe it is sufficient to remove the observation.*

Appendix 9.
Pearson's correlation

	PE	MTB	GROWTH	LEVERAGE	LIQUIDITY	GRUMMY	AER	SIZE	IDUMMY	NETCHG	REALPROP
PE	1.000										
MTB	0.100*	1.000									
GROWTH	0.014	0.050	1.000								
LEVERAGE	0.008	0.201***	-0.045	1.000							
LIQUIDITY	0.013	0.060	0.089	-0.262***	1.000						
GRDUMMY	0.019	-0.040	-0.139**	-0.067	0.104*	1.000					
AER	-0.023	0.188***	0.209***	-0.031	0.047	-0.003	1.000				
SIZE	0.084	-0.010	-0.068	0.020	-0.054	0.040	0.008	1.000			
IDUMMY	-0.006	-0.032	0.020	0.039	-0.052	-0.031	0.038	0.056	1.000		
NETCHG	-0.040	-0.019	0.112**	0.086	0.008	0.098*	0.045	-0.054	0.002	1.000	
REALPROP	0.036	-0.112**	-0.173***	0.194***	-0.008	-0.073	-0.028	0.113**	0.076	0.030	1.000

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

Appendix 10.
Distribution of estimated acquisition probability for targets and non-targets

Estimated acquisition probability		Target firms		Non-target firms		
Range	Median value (ρ)	Number	$f_1(\rho)$	Number	$f_2(\rho)$	$f_1(\rho)/f_2(\rho)$
0.000-0.074	0.037	1	1.3%	3	2.7%	48%
0.075-0.149	0.098	0	0.0%	2	1.8%	0%
0.150-0.224	0.187	2	2.6%	8	7.3%	36%
0.225-0.299	0.268	5	6.6%	12	10.9%	60%
0.300-0.374	0.347	13	17.1%	21	19.1%	90%
0.375-0.449	0.416	14	18.4%	33	30.0%	61%
0.450-0.524	0.487	23	30.3%	24	21.8%	139%
0.525-0.599	0.545	8	10.5%	4	3.6%	289%
0.600-0.674	0.618	7	9.2%	3	2.7%	338%
0.675-0.749	0.735	3	3.9%	0	0.0%	-
Total		76	100%	110	100%	