Bachelor's Thesis
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Risk Arbitrage

A study of predictive variables in Nordic corporate takeovers

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Abstract

The most critical element of doing risk arbitrage is the assessment of the outcome of a corporate takeover. Prediction models have been created in the past and successfully proven some variables in mergers and acquisitions to have a significant impact on the takeover outcome. However, these prediction models have mostly been created with U.S. data and some years back in time.

This thesis will investigate variables that previous studies have shown to have a predictive ability about the outcome of a corporate takeover and see if these previous findings are applicable in the Nordic markets as well. With the help of a logistic regression model, we have created a takeover prediction model based on a data sample containing 534 mergers and acquisitions in the Nordic markets over the period of 2000-2016. We found the variables time to completion, target size, percentage sought, toehold, attitude, private equity and competing bids to have a significant impact on the takeover outcome.

Keywords— Risk Arbitrage, Merger Arbitrage, Nordic Markets, Takeover Success Prediction, Mergers and Acquisitions

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1 Introduction

When a merger or acquisition is being announced to the public there is often a surge in the stock price of the target company due to the premium offered by the acquiring firm. However, as there are risks and uncertainties surrounding the bidder's ability to close the transaction, the target's stock price often trade below the offered price as the market is aware of these risks (Melka and Shabi, 2013, p. xxiv). The spread between the offered price and the market price is usually referred to as the arbitrage spread, or the merger spread. We will use the term arbitrage spread throughout the thesis. There are ways to profit from this spread, which has been noticed by event-driven hedge funds, that are now frequently pursuing this so-called merger arbitrage or risk arbitrage strategy to generate returns for their investors.

The practice of risk arbitrage is not by any means something new and has been pursued by investors since the 1940s when Gus Levy of Goldman Sachs developed the investment strategy (Melka and Shabi, 2013, p. xxiiv). The strategy has been shown to generate abnormal returns by several studies. For example, Baker and Savasoglu (2002) showed that a diversified portfolio of risk arbitrage positions could generate an abnormal return of 0.6-0.9% per month between 1981-1996.

The way risk arbitrageurs generate returns from the arbitrage spread differs and depends on the payment method used in each takeover. In pure cash deals, this is done by taking a long position in the target stock and then wait for the takeover to close and the target stock price to converge to the price offered by the acquirer. If there is a stock swap deal, the risk arbitrageur must take a long position in the target stock and simultaneously take a short position in the acquirer stock. These strategies will be explained in more detail in the theoretical framework of this thesis.

The biggest risk in pursuing a risk arbitrage strategy lies in the probability of a takeover failure. When the typical stock investor takes a position in the stock market, they are faced with an almost symmetric payoff distribution, as the probability of a certain gain is almost the same as the probability of an equally sized loss (Krichner, 2009, p. 9). Alas, the risk arbitrageur is not faced with the same symmetric payoff distribution as their distribution is left tail skewed. The reason for this asymmetric payoff distribution is that the risk arbitrageur is limited to the gain from the arbitrage spread, while the downside is considerably bigger and occurs if the takeover fails and the target stock falls back to its pre-announcement price.

Regardless of this asymmetric payoff distribution, investors are willing to take this risk as the probability of a large loss is very small and the probability of a small gain is very large (Krichner, 2009, pp. 9-10). Investment strategies with this type of payoff distribution can analogously be explained as "picking up nickels in front of a steamroller"; an expression made famous by Nassim Taleb in his book The Black Swan (2007, p. 204), as he expresses his concern for investors that engage in strategies with almost no volatility, but that contain the risk of a very large loss. Thus, it is of great interest to the practitioner of risk arbitrage to be aware of when that steamroller is too close, or expressed in a more serious way; when there is an overwhelming risk that the takeover will fail.

1.1 Purpose

The purpose of this thesis is to investigate predictive variables of the outcome in corporate takeovers in the Nordic markets of Sweden, Denmark, Norway, Finland and Iceland. By using a logistic regression model on a data sample containing 534 mergers and acquisitions over the period of 2000-2016 in the Nordic markets, we will create a prediction model that can be applied to the practice of risk arbitrage.

1.2 Motivation and Contribution of the Thesis

The motivation behind this thesis is to investigate variables that has predictive abilities of the outcome regarding corporate takeovers in the Nordic markets. These predictive variables will be the foundation of a takeover prediction model. Previous studies have mainly focused on the U.S. takeover market, and there are to our knowledge no previous study that has investigated the prediction of takeover success in the Nordic markets. Our sample stretches over the period of 2000-2016 and consists of a data set of 534 takeover bids.

By using a logistic regression model, we manage in this thesis to create a takeover prediction model that can be applied in the Nordic markets. We manage to strengthen previous findings that the variables time to completion, target size, percentage sought, toehold, attitude, private equity and competing bids have a significant impact on the takeover outcome. Our findings can be of great interest to investors that engage in risk arbitrage activities, as well as senior management of companies that seek acquisitions in the Nordic markets.

1.3 Limitations to the Thesis

This study is limited to takeover bids made on targets listed in the Nordic markets between January 1st, 2000 and December 31st, 2016. The data is selected out of criterions such as the target firm is a public company and listed on a stock exchange in any of the above-mentioned Nordic countries. The takeover technique is a merger or an acquisition and the percentage of shares sought must yield control of the company. All minor acquisitions such as investments were excluded. This means that the acquirer strives to own more than 50% after the completion date. We have also limited our data to takeovers that have been paid with either cash, stock or a combination of cash and stock. Furthermore, the limitation of available data has forced us to exclude some independent variables that we initially planned to include in our prediction model. These excluded variables are further discussed in section 4.6.

1.4 Outline

The remainder of this thesis is organized as follows. Chapter two discusses the underlying definitions and theory. Chapter three will review some of the most prominent previous research that this thesis is associated with. Chapter four will present our data and the logistic regression used in this thesis. Chapter five will present the regression results and the associated discussion. Lastly, chapter six will conclude our study and present suggestions for further studies.

2 Theoretical Framework

This chapter will give the reader a more in-depth review of the theoretical framework which this thesis is built upon. It will explain the role of mergers and acquisitions, arbitrage, the strategy used by risk arbitrageurs as well as the risk-return relationship that signifies risk arbitrage.

2.1 Mergers and Acquisitions

Corporate control is defined as the legal right to allocate the corporate resources (Jensen and Ruback, 1983) which stipulate the foundation of the takeover market theory, developed by Manne (1965). The market for corporate control has become highly competitive due to the belief that other groups of management can utilize the resources in a better way and so forth create more value of the company (Manne, 1965). A previous study has shown that companies with a more efficient allocation of resources have a higher share price in the open market relative to companies with inefficient allocations (Manne, 1965).

Corporate takeovers can be done by three different takeover methods: tender offers, mergers or proxy fights. Berk and DeMarzo (2014, p. 931) define a merger as a consolidation of the equally sized companies and a tender offer as an acquisition of a smaller company relative its size, by purchasing its shares. As mention above, a tender offer refers to the purchase of target company shares by either going to the open market or directly purchase from large investors, making it possible to compulsory acquire the residual shares (Manne, 1965). Unlike a tender offer, a merger is often referred as a negotiation between the acquiring company's management and target company's management, and usually involves a stock swap as payment (Straub, 2007, p. 15). A proxy fight occurs when the acquisition is regarded as hostile and where the acquirer pursues the shareholders to vote for changes to the board, where the acquirer's candidates get seats (Berk and DeMarzo, 2014, p. 1059). In this thesis, we will use the word takeover for all sorts of mergers and acquisitions.

Mergers and acquisitions occur in waves over time which are usually characterized by a high takeover frequency in times of economic expansion (Berk and DeMarzo, 2014, p. 931). Andrade et al. (2001) suggest that the wave clustering is due to unexpected industry-wide shocks. The underlying reason for mergers and acquisitions is to take advantage of synergies between the two firms. Usually, these synergies fall into either cost reduction or enhancement of revenue (Berk and DeMarzo, 2014, p. 934).

According to Jensen and Ruback (1983), shareholders are assumed to have a passive role whereas the acquirer has the power to utilize corporate resources and restructure management and therefore the company's value. Melka and Shabi (2013, p. xxv) state that the risk arbitrageur's role is to evaluate and value the announced takeover and act as intermediaries for the current shareholders. Their importance is due to their presence and the increased trading volume that yields. Their provision of liquidity (trading volume) is an opportunity for investors, which cannot bear the completion risk, to sell their shares and realize a profit. In the absence of risk arbitrageurs, potential profits could evaporate if the probability of failure would increase (Melka and Shabi, 2013, p. 67).

2.2 Definition of Arbitrage and Risk Arbitrage

The formal definition of arbitrage is the process of a self-financed trading strategy, which generates positive returns without any risk; there is a certainty that no negative cash-flow will occur in any state (Hull, 2015, p. 14-15). Academia has come up with the assumption of arbitrage-free pricing, due to the arbitrage activity in the marketplace. This holds due to the forces of supply and demand when an arbitrageur tries to exploit price discrepancies and the price converges into equilibrium. In addition to this, academia points out that there exists no free lunch in the financial markets (Kirchner, 2009, pp. 3-5).

The definition of arbitrage, used by industry practitioners (e.g. traders) is not in line with the definition stipulated by academia. The former has a less strict definition, where arbitrage is a strategy where the expected return is strictly positive and self-financing is not a requirement (Hull, 2015, pp. 14-15; Schlefiner and Vishny, 1997).

Kirchner (2009, p. 5) points out that arbitrage strategies that lack market risk but has exposure to other types of risks are regarded quasi-arbitrage strategies. Bodie et al. (2014, p. 931) point out that market risk can be hedged by selling futures on the stock market index although it still exists a risk exposure in risk arbitrage, therefore its name, which is the event risk. The event risk refers to the completion risk, that the takeover will be withdrawn or terminated and potential returns will evaporate (Kirchner, 2009, p. 5-6).

Kirchner (2009, p. 5) argues that risk arbitrageurs is in fact practicing arbitrage, even though academia says the opposite. Brown and Raymond (1986) argue that risk arbitrageurs are practicing speculation, although Kirchner (2009, p. 5) says that the difference between a speculator and an arbitrageur is the knowledge of buy and sell prices. The latter has, at least in theory, knowledge of which price to sell and buy and the former is exposed to a great amount of uncertainty. Kirchner (2009, p. 6) therefore, concludes that risk arbitrage involves less risk than speculation, but it is not risk-free and therefore falls out of the scope of the academic definition.

2.3 The Risk Arbitrage Strategy

The investment process or strategy, pursued by risk arbitrageurs will differ depending on the payment method used for the transaction (Melka and Shabi, 2013, p. 33). This section will explain the different strategies used by risk arbitrageurs when pursuing risk arbitrage.

Cash Mergers

A cash merger is the most straight forward type of merger and is defined as a transaction where a buyer proposes to buy the shares of a target company with a pure cash payment. The difference between the stock price and the offered price at the announcement date is called the arbitrage spread. In a cash merger situation, the risk arbitrageur simply takes a long position in the target company, then wait until the transaction completes and gain the offered value for their shares (Kirchner, 2009, pp. 13-14). The return of the trade will be the arbitrage spread.

Stock-for-Stock Mergers

A more complex trade for the risk arbitrageur occurs when the merger transaction is paid with stock, or a combination of cash and stock. Instead of a fixed factor of cash per target share the acquiring company is now offering a fixed number of their share per target company share as payment. In this type of situation, the risk arbitrageur cannot just simply buy the target stock and wait for the merger to complete, as the market price of the acquiring company's stock might fluctuate until completion. Thus, the risk arbitrageur does now have to buy the target stock and simultaneously take a short position in the stock of the acquiring company (Kirchner, 2009, pp. 20-22). The return from this trade will be the difference in cash flow between the long and the short position. To make this situation even more clear to the reader we will provide a short example taken from our data sample.

On the 2nd of October 2000, the Danish company Danske Bank A/S placed a bid on RealDanmark A/S offering 4.144 of their share per every target share, indicating a total deal value of about DKK 24887.01 million. On the 28th of March 2001, the takeover was completed. In this situation, the risk arbitrageur cannot just buy shares in RealDanmark A/S and hope for the transaction to complete. When the transaction completes, the investor would then receive 4.144 of Danske Bank A/S shares to sell at the market price. This is not considered an arbitrage as the market price could be higher or lower, compared to the price at the announcement date. Instead, the risk arbitrageur must take a long position in RealDanmark A/S, and simultaneously take a short position in Danske Bank A/S.

On the announcement day, RealDanmark A/S share price closed at DKK 426.00, and Danske Bank A/S closed at DKK 104.00. If the risk arbitrageur establishes a position on the announcement day, he takes a long position in 100 shares of RealDanmark A/S at DKK

426.00 and a short position of Danske Bank A/S of 414.4 shares at DKK 104.00. This yields an initial positive cash-flow of DKK 497.6. At completion date, the RealDanmark A/S shares get converted to 4.144 shares of Danske Bank A/S which can be used to cover the short position. This is in line with the arbitrage definition which was explained earlier in this chapter.

Mergers with Collars

An even more complex trade for the risk arbitrageur occurs when the merger transaction includes a payment agreement with a collar, meaning that the acquirer's stock price can fluctuate between an upper and a lower limit without affecting the final price paid to the target company's shareholders. The implications for the risk arbitrageur in transactions with such agreements are that the arbitrageur must be prepared to hedge his positions dynamically to secure a return from the trade (Kirchner, 2009, p. 35).

2.4 Risk-Return Relationship in Risk Arbitrage

The risk arbitrageur faces the risk of an unsuccessful takeover, where the target share price often plunge to price levels prior to the announcement (or even lower). Mitchell and Pulvino (2001) state that risk arbitrage has a pay-off equal to writing put options on an index, a limited upside and a huge downside. In their research, they conclude that the risk-reward-relationship in risk arbitrage is non-linear.

Previous papers have documented a wide range of abnormal returns generated from risk arbitrage strategies. Baker and Savasoglu (2002) have found annualized excess returns of 12.5%, and Mitchell and Pulvino (2001) report 10.3% in annualized excess returns. The former state that the underlying reason for these returns is that there is not enough sufficient capital to erase these arbitrage opportunities (Baker and Savasoglu, 2002). The latter report that transaction costs might have a great impact on the return, which is not accounted for in studies. They also suggest that the abnormal returns are compensation for bearing additional risk (Mitchell and Pulvino, 2001).

Baker and Savasoglu (2000) point out that risk arbitrageurs act as insurance providers for the shareholders in the target company, since they can bear the event risk that other investors cannot. Capital markets, in theory, should incorporate the bid immediately. This does not happen due to the absence of risk bearing investors, creating an oversupply of sellers, and pushes the share price downwards, creating a spread which is exploited by risk arbitrageurs (Shleifer and Vishny, 1997). Therefore, Mitchell and Pulvino (2001) conclude that the abnormal excessive returns are in fact liquidity and completion risk premiums. Mitchell and Pulvino (2001) conclude that usage of linear models such as the Capital Asset Pricing Model is not applicable to this strategy. Glosten and Jagannathan

(1994) suggest the usage of contingent claims to capture the nonlinearity to measure its ability to generate abnormal returns.

Recent research has shown differences in the risk-return-relationship between market participants. Cao et al. (2016) conclude that hedge funds possess superior skills in assessing the expected outcome of corporate takeovers compared to non-hedge funds. They point out that the source of abnormal excessive returns is their risk management regarding avoidance of takeovers which has the greatest tail events.

3 Previous Research

This chapter will present a chronological review and go more into detail of the, in our opinion, most prominent previous literature about risk arbitrage, takeover predictions, and the methods of creating prediction models.

3.1 Hoffmeister and Dyl (1981)

In 1981 Hoffmeister and Dyl published an article in the journal *Financial Management* called Predicting Outcomes of Cash Tender Offers. The purpose of the paper was to build a predictive framework to determine the likelihood of successful corporate takeovers.

Data Description and Methodology

Their data sample consisted of 84 cash tender deals over the period of 1976-1977 and was based on the U.S. market. Their initial model used 17 explanatory variables and their statistical framework was a multivariate discriminant analysis. They excluded all takeover offers where the outcome was not disclosed or when the percentage of acquired shares was smaller than the percentage sought.

The explanatory variables were divided into three major groups. In the first group, the researchers included: current ratio, dividend growth two years prior the takeover attempt, dividend yield, earnings growth two years prior the takeover attempt, payout ratio, P/E-ratio, profit margin and return on equity. The second group consisted of the variables: transaction size, target firm's market capitalization, current toehold of the acquiring firm, bid premium two weeks prior the announcement and the ratio between bid premium and book-value. The third group of explanatory variables consisted of the current ratio compared to industry peers, comparative profit margin and comparative return on equity. Hoffmeister and Dyl had a categorical variable regarding the attitude of the target management towards the takeover offer.

Results

Hoffmeister and Dyl used a set of varieties of models to test which combination of explanatory variables could predict the outcome most accurately. They found that attitude towards the takeover offer from the target's management and the target market capitalization was strongly associated with successful offers. They concluded that hostility towards the takeover have significant effect on the probability of failure.

3.2 Walkling (1985)

In 1985 in *The Journal of Financial and Quantitative Analysis*, Ralph A. Walkling published his paper Predicting Tender Offer Success: A Logistic Analysis. The scope of the paper was to develop a prediction model of the outcome of tender offers and to investigate the bid premium anomaly.

Data Description and Methodology

Walkling collected a data sample consisting of 158 observations, mainly from the database of filed tender offers provided by the Security and Exchange Commission (SEC) over the period of 1972-1977. Takeover specifics were received in the prospects from each party of the transaction. Additional information such as time series of stock prices were obtained from Standard & Poor's Stock Price Guide. Other additional information was obtained by screening through magazines and journals associated with business and finance.

The data set was divided into an in-sample set and an out-sample set, to assess prediction accuracy of the model. The latter consisted of 108 observations and the former of 50 observations. The author of the paper applied econometric techniques such as linear modeling and logistic regression to the data set.

One of the main points of Walkling's paper was the importance of an appropriate specification of the bid premium. He embraced the question of from which date, the bid premium percentage should be calculated. Walkling shows that previous research has used the date in which the acquiring firm filed to the Security and Exchange Commission as their reference date. In his empirical research, he showed that more than 40% of the investigated takeovers had announced their intentions and takeover specifics in the financial press before they officially filed to the Security and Exchange Commission. Walking says that these type of actions has led to incorporation of information to the target's share price and therefore misled the calculation of bid premium and its predictive power. The author argues that bid premiums should be calculated on the market price 14 days prior filing the Security and Exchange Commission, or at the announcement date. Walking also adds that the calculation needs to take the percentage sought into account when calculating the bid premium.

Results

Walkling concluded that previous research and its anomalous findings of bid premiums is a result of specification errors. As previous research did not account for the early announcement in the press and therefore their estimations of the bid premium are biased and faulty.

3.3 Branch and Yang (2003)

In 2003 Branch and Yang published a paper called Predicting Successful Takeovers and Risk Arbitrage in the *Quarterly Journal of Business and Economics*. In their study, they created a prediction model for the outcome of a takeover attempt and explicitly explored the impact of different payment methods, such as cash, stock, or deals with a collar agreement.

Data Description and Methodology

In their study, they investigated 1,097 takeovers with cash, stock, and collar payments over the period of 1991-2000. The data was gathered from five main databases: SDC, Data Stream, CompuStat, 8-K files from the Security and Exchange Commission and Lexis-Nexis. They created a prediction model using a stepwise logistic regression which included several variables that previous literature had found significant and their own variable of interest, different payment methods.

Investigated variables (excluding payment) were relative target size, target debt ratio, bid premium, attitude, arbitrage spread, percentage sought and an interaction variable between attitude and arbitrage spread. After creating the model, Branch and Yang also tested it to an out-of-sample test to support the effectiveness of the model.

Results

Branch and Yang found in their study that cash payments tend to increase the likelihood of a successful takeover attempt, compared to stock swap deals. They also found that in stock swap deals, a collar (range of exchange ratios) improved the success rate compared to those deals with a fixed exchange ratio.

3.4 Branch and Wang (2009)

Branch and Wang published a paper called Takeover Success Prediction and Performance of Risk Arbitrage in the *Journal of Business & Economic Studies* in 2009. The purpose of their study was to create a takeover success prediction model by investigating several variables and their roles in the outcome of corporate takeovers. They did also investigate the implications of risk arbitrage performance when using a pair-matched sample, as well as a weighted logistic regression when running their model.

Data Description and Methodology

Branch and Wang based their study on U.S. data covering 1,313 takeovers over the period of 1995-2005. Using a logistic regression model Branch and Wang tested 11 variables to see whether they could find any of the variables to be predictive regarding the outcome of the takeover. They divided their data into two subsamples to test the difference in performance of the model when using an un-weighted logistic regression or a weighted logistic regression. Following variables were included in their model: target price run-up, target size, attitude, arbitrage spread, competing bids, the percentage of shares sought, toehold, termination fees, payment type and bid premium.

After creating their prediction model, they tested the performance of the model by establishing positions in takeovers that the model found to have positive expected return, based on the probability of takeover failure. This test was done from the estimates using a pair-matched sample, as well as a weighted logistic regression and an un-weighted logistic regression to investigate performance differences.

Results

Branch and Wang found that a pair-matched sample will bias the parameter estimates, the prediction of the takeover outcome and thus also bias the expected return of the risk arbitrage strategy. Further, they found that a weighted logistic regression will remove the bias and adjust the probability estimates in the model. The variables that had a significant effect on the takeover outcome was target price run-up, target size, attitude, the arbitrage spread and competing bids. Target price run-up and the arbitrage spread were only significant at the level of 10%.

As a conclusion, Branch and Wang recommend risk arbitrageurs to be careful when using a pair-matched sample when creating a prediction model. They also recommend practitioners to use a weighted logistic regression as it will give more reliable results and enhance the performance of a risk arbitrage strategy.

4 Empirical Framework and Data Sample

This chapter will present the reader with the scientific approach and general methodology, the data that has been used in our study, a description of the variables, as well as a presentation of the statistical method used.

4.1 Scientific Approach and General Methodology

A quantitative approach involves a systematic inquiry where statistical and mathematical procedures are utilized to analyze the data. Contrary to the quantitative approach there is the qualitative approach which emphasises theory rather than the significant results (Bryman and Bell, 2007, p. 28). As the scope of this thesis is to evaluate predictive variables in corporate takeovers, the usage of mathematical and statistical procedures to analyze the data makes the quantitative approach appropriate to match the purpose of this thesis. Bryman and Bell (2007, pp. 11-15) point out that a deductive approach is appropriate when the present study analyzes empirical data based on an already existing theoretical framework. This is in line with the scope of this thesis and therefore, an appropriate approach.

At an early stage in the process, extensive research was conducted by reading literature and other research papers and publications about risk arbitrage, as well as about takeovers in general and prediction of the takeover outcome. By doing so, we have accumulated a foundation of knowledge that has helped us to take a suitable approach to the subject and the phenomenon that we wanted to investigate.

After that, a process of gathering data was initiated. We used the Mergers & Acquisitions module hosted by Bloomberg Finance L.P. for the takeover specifics. This data was later mated to the Bloomberg Excel Add-in which enabled us to receive time-series data consisting of historical prices for each takeover. This was later stored in an MS Excel database. To structure and clean the data appropriately we used VBA programming in the MS Excel software. The econometric analysis was utilized using the statistical programming language R and the software R-studio and appropriate third party statistical packages. After the regression analysis had been done, the final output was dissected and analyzed from the theoretical framework.

4.2 Data Selection

The data in this study are primarily gathered from the Bloomberg terminal and its MA module. From the MA module, we have collected all the corporate takeovers in our data sample, as well as all investigated variables, except target's stock price run-up. Target's stock price run-up is calculated using the Bloomberg Excel Add-in and further explained in subsection 4.5.

Our data sample consists of 534 successful and unsuccessful takeover attempts with a resolution date between January 1st, 2000 and December 31st, 2016. The search criteria used in the Bloomberg MA module are the following:

- Target company must be public and listed on any of the Danish, Swedish, Norwegian, Finnish or Icelandic stock market
- The deal status can be either completed, withdrawn, or terminated
- Percentage sought by the acquiring company must be between 40 and 100 percent
- Payment type can be cash, stock or a combination of cash and stock

Our chosen period, 2000-2016, will take economic expansions and recessions into consideration (including the financial crisis of 2007-2008, as well as the burst of the dot-com bubble during 2000-2002) which will make our results independent of specific market conditions, and thus give us more robust and reliable results. To match the purpose of this thesis our geographical limitation is set to targets listed in any of the above-mentioned Nordic markets.

To exclude deals where only a minority stake is sought, and in which it is not possible to pursue risk arbitrage, we have limited our data to transactions where the buyer is trying to acquire at least 40% of the target company, and where the acquirer strives to own more than 50% after the completion date.

In line with previous studies, we are limiting the payment method in our data sample to either cash, stock or a combination of cash and stock. This is done due to the complexity of the payment structure that includes debt or derivative instruments.

Our initial data consisted of 710 takeovers, which were reduced to 534, due to lack of some variables in the data. Transactions in which the announcement date and the resolution date occurred on the same date has been omitted due to the impossibility of doing risk arbitrage in those takeovers. Takeovers that did not present any deal value was also omitted, as well as deals where the arbitrage spread was not possible to calculate due to lack of information about the offered share price.

4.3 Econometric Model

The outcome of a corporate takeover is binary, it either fails or succeeds. To determine the probability of a certain outcome, a logistic regression model can come handy. If the takeover is successful, then $Y = 1$ and if not $Y = 0$. The logistic regression model has advantages over linear models such as ordinary least squares, due to its relaxation of assumptions. The logistic regression model is commonly used in previous research regarding prediction of takeover success.

Logistic Regression

The logistic regression model is based on the fact that the dependent variable is a categorical, in our case binary as the outcome is either success or fail. The logistic function comes into play since it maps any real number into a range $[0, 1]$ and hence can be interpreted as a probability. This violates the underlying assumptions of linear regression models such as ordinary least squares, as it does not need normality in residuals nor homoscedasticity in the data (Menard, 2002, pp. 4-5). The probability of success and failure is defined as follows:

$$Pr(Y_i = 1) = \pi_i \tag{1}$$

$$Pr(Y_i = 0) = 1 - \pi_i \tag{2}$$

We can rewrite equation (1) and (2) as follows:

$$Pr(Y_i = y_i) = \pi_i^{y_i}(1 - \pi_i)^{1-y_i} \tag{3}$$

The logistic regression takes advantage of the linear regression and the logit link, such that a linear regression model becomes transformed. The transformed linear regression model is defined as follows, where X_i' is the vector with independent variables and μ is the vector with coefficients to be estimated:

$$\pi_i = \frac{\exp(X_i'\mu)}{1 + \exp(X_i'\mu)} \tag{4}$$

We can therefore write the relationship between the logit and the linear regression as follows:

$$\ln \frac{\pi(X_i)}{1 - \pi(X_i)} = X_i'\mu = \beta_0 + \beta_1 x_{i,1} + ... + \beta_k x_{i,k} \tag{5}$$

To interpret the effect of a change in the independent variable, it is crucial to investigate the odds-ratio of the estimated coefficient. The odds-ratio (OR) is defined as follows:

$$OR = \frac{\pi(X_i + \Delta)/1 - \pi(X_i + \Delta)}{\pi(X_i)/1 - \pi(X_i)} = \exp(\beta_0 + \beta_1 x_{i,1} + ... + \beta_k x_{i,k}) \tag{6}$$

Maximum Likelihood Estimation

To estimate the regression coefficients, the logistic regression takes advantage of the maximum likelihood estimation. Since there exists no closed-form solution to this estimation, the algorithm relies on the iterative Newton-Raphson method (Hosmer et al., 2013, p. 9).

The method of maximum likelihood relaxes on the assumption that our data sample has a probability distribution with some unknown vector parameter μ. The method of maximum likelihood will find a point estimator $u(x_{i,1}, ..., x_{i,k})$ of μ with the observed values from our sample $(x_{i,1}, ..., x_{i,k})$. The concept is based on maximizing our estimate such that the likelihood of obtaining the data we already observed. Therefore, we will use our sample and its probability mass function to create a joint probability mass function over our sample and label that as the likelihood function (Dougherty, 2011, pp. 380-384).

$$\hat{L}(\mu) = f(X_1; \mu) \cdots f(X_k; \mu) = \prod_{i=1}^{k} f(X_i; \mu) \tag{7}$$

To obtain the likelihood, we maximize the function $\hat{L}(\mu)$ with respect to μ. By exploiting the ever-increasing property of the logarithmic functions, we convert the likelihood function to a log-likelihood function.

$$\log \hat{L}(\mu) = \log f(X_1; \mu) + ... + \log f(X_k; \mu) = \sum_{i=1}^{k} \log f(X_i; \mu) \tag{8}$$

The value of μ which maximizes $\log \hat{L}(\mu)$ is obtained by the first derivative of the log-likelihood function by using the first order condition (Hosmer et al., 2013, p. 9).

$$\frac{\mathrm{d} \log \hat{L}(\mu)}{\mathrm{d}\mu} = 0 \tag{9}$$

When the maximum likelihood estimation has completed its iterative process, the process is said to converge. Although the absence of convergence indicates that the coefficients are not valid since the algorithm could not find appropriate solutions. That could be the cause of perfect multicollinearity in the parameters estimated (Hosmer et al., 2013, p. 90).

Every statistical model relies on assumptions. If the assumptions of the logistic regression analysis are violated problems arise. These violations can cause problems such as biased estimates and abnormal large standard errors which might affect our statistical inferences. Therefore, this section will assess goodness-of-fit and diagnose potential problems regarding our model.

Deviance and Likelihood-ratio Tests

Menard (2002, p. 20) highlighted the absence of sufficient measures for discrimination for logistic regression analysis, compared to linear regression analysis where R^2 is the general measure. Therefore, the deviance and the likelihood-ratio are used to assess the goodness-of-fit of logistic regression models. Deviance measures the lack of fit to the data in the logistic regression model (Hosmer et al., 2013, p. 155). Deviance is defined as follows:

$$D = -2 \log \frac{(\text{model fitted of likelihood})}{(\text{model saturated of likelihood})} \tag{10}$$

Usually, there exists no saturated model, which implies that the Deviance must be calculated solely with the fitted model.

$$D = -2 \log(\text{model fitted of likelihood}) \tag{11}$$

To assess the contribution of a dependent variable or a set of dependent variables, one can use the difference between null deviance and model deviance. The former is the difference between a model with only an intercept and the saturated model. The latter is the difference between a model with at least one predictor and the saturated model (Cohen et al., 2003, p. 507).

$$D = -2 \log \frac{(\text{model null of likelihood})}{(\text{model fitted of likelihood})} \tag{12}$$

To test if the fitted model has a better fit than the null model, a Chi-square test is used. Menard (2002, pp. 21-23) says that the likelihood-ratio test involves comparing the deviance of the null model and the fitted model, where the Chi-square statistic is calculated by the difference in degrees of freedom. This test can be extended to compare the goodness-of-fit between two different models.

Pseudo R^2 McFadden and Adjusted Pseudo R^2 McFadden

As mentioned above the R^2 measure is not appropriate in the cases where maximum likelihood estimation is used to estimate the coefficients. Therefore, a set of pseudo R^2 measurements have been developed (Freese et al., 2006, p. 84). One measure is the pseudo R^2 McFadden, which is known as a likelihood index. The measure is defined as follows:

$$R^2_{McF} = \frac{\ln \hat{L}(M_{null}) - \ln \hat{L}(M_{predictor})}{\ln \hat{L}(M_{null})} = 1 - \frac{\ln \hat{L}(M_{predictor})}{ln\hat{L}(M_{null})} \tag{13}$$

The model labeled $M_{predictor}$ refers to the model with one or more predictors, excluding the intercept. The model labeled M_{null} refers to the model with only the intercept. When a model has a bad fit, the likelihood tends to be a small value, which implies that the natural logarithm of that likelihood tends to be bigger relative to the other model and its transformed likelihood value. Therefore, a ratio which is close to zero indicates a good fit of the model with predictors, since the null model will always fit poorly compared to the model with predictors (Freese et al., 2006, p. 84).

Freese et al. (2006, p. 84) argue that the pseudo R^2 McFadden measure is analogous to the ordinary R^2 and due to that the measure needs to be adjusted. The measure tends to increase when additional predictors are added, similarly to the R^2. Therefore, it is of interest to investigate the adjusted pseudo R^2 McFadden. The adjusted pseudo R^2 McFadden measure is defined as follows (K is the number of predictors):

$$R^2_{McF} = 1 - \frac{\ln \hat{L}(M_{predictor}) - K}{ln\hat{L}(M_{null})} \tag{14}$$

Multicollinearity

The absence of convergence in the maximum likelihood estimation can be a result of multicollinearity, an unsatisfying high correlation between predictors. Multicollinearity affects the standard errors of the coefficients and therefore decreases the probability of convergence (Hosmer et al., 2013, p.90). Multicollinearity also hampers the ability to discern the effect of one sole predictor on the independent variable (Brooks, 2014, p. 217). To assess if there exists multicollinearity, the Variance Inflation Factor (VIF) is a good test. VIF measures the changes in the variance of the predictors due to multicollinearity (Gujarati, 2011, p.70). This test is used by Branch and Wang (2009) when they selected their independent variables for their prediction model.

4.4 Dependent Variable

The outcome of the takeover attempt is the dependent variable in our logistic regression, and can only take the values "1" or "0", completed or terminated/whitdrawn respectively. The data are taken from Bloomberg's MA module where the two outcomes are defined as follows: "Completed: a completed deal has been consummated and no longer needs approvals. Terminated: a terminated deal has been dissolved and does not continue".

4.5 Predictive Variables

This subsection will lead the reader through the independent variables used in our logistic regression, how they are coded, how they are defined and previous findings regarding their predictive abilities. For a more in-depth description of the used variables taken from Bloomberg's MA module, we recommend the reader to see Bloomberg's HELP MA module and the definitions section.

Target Size

Branch and Yang (2003) and Branch and Wang (2009) found that the relative size of the target company is negatively related to the success rate of the takeover attempt. Hoffmeister and Dyl (1981) did also investigate the impact of target size, but with an absolute size approach. They found that a larger absolute market value of the target decreased the success rate of the takeover attempt. Further studies that tested the log of the target's size, done by Cotter et al. (1997) and Schwert (2000), could not find a significant relationship between the target's size and the takeover success. As we are investigating takeovers with both private and public acquirers, it is not possible for us to take a relative size approach and we will follow the practice of Hoffmeister and Dyl (1981) and look at the absolute market value of the target.

The value of the transaction is described in the Bloomberg terminal as the total dollar value of the entire offer, which includes all disclosed payment types. We expect the target size to be negatively related to the probability of a successful takeover.

Attitude

In some situations, the management or board of the target company decides to reject the takeover approach from the potential acquirer. When this happens, but the buyer persists with the takeover, the takeover is usually referred to as hostile (Melka and Shabi, 2013, p. 63). Relative target size, together with the target's attitude towards the takeover (friendly or hostile) is per Branch and Yang (2003) the most significant variables in predicting the takeover outcome. Branch and Wang (2009) did also find the attitude as one of the most significant factors affecting the outcome of a takeover. These findings are supported by Hoffmeister and Dyl (1981) who found that the attitude towards the takeover is one of several major factors affecting the success of takeover attempts.

In our data, we have coded "1" for transactions that Bloomberg considered friendly and "0" for transactions that they considered hostile. We expect friendly takeovers to increase the probability of a successful takeover.

Bid Premium

When a buyer places a bid at a target company, that bid is usually placed at a premium over the current market price, as they often anticipate cost savings and other synergies when integrating the target company into their own business (Berk and DeMarzo, 2014, pp. 934-940). Walkling (1985) found, at the time contrary to prior research, that the bid premium size does indeed have a significant impact on the outcome of the takeover attempt and argues that prior research was guilty of specification errors. Walkling (1985) does also refer to economic theory and writes that if a bidder is facing an upward-sloping supply curve when acquiring shares in a target, they would have to pay a premium to secure a successful transaction. However, more recent research conducted by Mitchell and Pulvino (2002), Baker and Savasoglu (2002) and Branch and Wang (2009) do not find the bid premium size to have a significant effect on the takeover outcome.

Bid premium is taken from the Bloomberg terminal and is expressed as the premium offered by the buyer over the target average share price one week prior to the announcement date. We expect to find a positive relationship between the size of the bid premium and the probability of a successful takeover.

Rivalry Bids

Walkling (1985) found that multiple bids by several prospective buyers will decrease the probability that any bid will be successful. This finding is supported by Branch and Wang (2009). Even though rivalry bids have been found to decrease the probability of a successful takeover they are a great source of revenue for the arbitrageur who took a position in the stock just after the initial offer was made public (Melka and Shabi, 2013, p. 71).

Rivalry bids is a dummy variable that takes the value "0" if a third party did launch an offer for the target company while the initial bid was pending and the value "1" if there were no competing bids. This data were gathered from the Bloomberg terminal. We expect the absence of a third-party rivalry bid to increase the probability of a successful takeover.

Target's Stock Price Run-up

A so-called target stock price run-up, referred by Branch and Wang (2009) as the cumulative abnormal return in the target's stock price prior to the announcement date, has been shown by the same authors to have a significant positive relationship to the probability of a successful takeover. Narayanan et al. (2001) have also showed that trading volume increase in the target's share prior to the announcement.

When calculating the target's stock price run-up, we have followed Branch and Wang (2009) and studied the price run-up for 15-1 days prior to the announcement date. We used Bloomberg's Excel Add-in to get the historical price data for each target stock, as well as applicable benchmark index and the risk-free rate. To calculate the abnormal return, we have used the single index model (Bodie et al., 2014, p. 259):

$$r_{it} - r_f = \alpha_i + \beta_i(r_{mt} - r_f) + \epsilon_{it}$$

- r_{it} is the return of stock i at time t
- r_f is the risk-free interest rate
- r_{mt} is the market return at time t
- α_i is the abnormal return of stock i
- β_i is the correlation to the market for stock i
- ϵ_i is a disturbance term

The market returns in the model is the OMXS30 for Swedish targets, OMXC20 for Danish, OMX Iceland 8 Cap for Icelandic, OMX Helsinki 25 for Finnish and OBX for Norwegian targets. As the risk-free rate, we have used the inter-banking interest rate for each country, so for example, if the target is listed in Sweden we have used STIBOR as the risk-free rate, CIBOR for targets listed in Denmark, etc. We have then compared the observed target stock returns with the returns from the single index model and thus got the abnormal returns that we then have summed to get the cumulative abnormal return. We expect to find a positive relationship between a stock price run-up in the target prior to the takeover announcement and the probability of a successful takeover.

Leverage

Higher levels of leverage in the target company have been shown to be negatively related to the probability of a successful takeover attempt. Raad and Ryan (1995), as well as Branch and Yang (2003), have used a debt-to-assets ratio, whereas Schwert (2000) used a debt-to-equity ratio. Regardless of chosen leverage ratio, all the studies mentioned above found that the leverage of the target is negatively related to the success rate of the takeover attempt. We will follow the practice of Schwert (2000) and use the debt-to-equity ratio as a measure of financial leverage.

Financial leverage has been gathered from the Bloomberg terminal which defines financial leverage as net-debt-to-equity for the latest quarterly report prior to the announcement date. We expect to find a negative relationship between the financial leverage of the target and the probability of a successful takeover.

Arbitrage Spread

The risk arbitrage spread is the difference between the post-announcement market share price of the target and the bid offered by the acquirer. Thus, the risk arbitrage spread can be thought of as a discount by the market due to the risk that the acquisition might fail (Melka and Shabi, 2013, p. 257). Samuelson and Rosenthal (1986) and Brown and

Raymond (1986) found that the movements in the target stock price (i.e. the size of the risk arbitrage spread) are informative of the outcome of the takeover attempt. This is further supported by Branch and Wang (2009) who found the arbitrage spread to have a significant effect on the takeover outcome, where a larger spread decreases the probability of a successful takeover.

In our data, the arbitrage spread is defined as the percentage difference between the offer price and the target's closing share price two days after the announcement. The reason for using the closing price two days after the announcement date is so that the market should be able to incorporate all the information fully. This method is in line with Branch and Wang (2009). The target price per share offered by the buyer is taken from the Bloomberg's MA module and can there be found as cash terms as well as stock terms. For the stock terms, we have used the Bloomberg Excel Add-in and downloaded the closing price of the acquiring company one day prior to the announcement and used that to convert the stock terms to an offered price per share. We expect to find a negative relationship between the size of the arbitrage spread and the probability of a successful takeover.

Payment Method

A merger or acquisition can be paid in different ways with the most common being cash, stock, or a combination of the two. Pure cash offers are considered more attractive to the target shareholders as they will know exactly the price they will be paid, compared with a stock offer where the final price will depend on fluctuations in the acquirer's stock price (Melka and Shabi, 2013, p. 10). Branch and Yang (2003) found that cash transactions have a higher probability of success than stock swap deals. They also found that stock swap deals with a range of exchange ratios, also called a collar, increase the probability of a successful acquisition, compared to a stock swap with a fixed exchange ratio.

We have looked at transactions paid with cash, stock, or a combination of both. The method of payment is a dummy variable that takes the value "0" if the transaction was paid with stock or a combination of cash and stock, and "1" if the transaction was only paid with cash. The data were gathered from the Bloomberg terminal. We expect takeovers that are only paid with cash to have a higher probability of success, compared with takeovers paid with stock, or a combination of cash and stock.

Percentage Sought by Acquirer

Branch and Yang (2003) found a negative relationship between the transaction size, i.e. the percentage of shares sought and the probability of success. In other words, the greater percentage of the total outstanding number of shares that the buyer seeks to acquirer, the smaller the chance of a successful attempt.

The data are received from the Bloomberg terminal and defined as the percentage of shares sought by the acquirer in the transaction. We expect to find a negative relationship between the percentage of shares sought by the acquirer and the probability of a successful takeover.

Time to Completion

The time between the announcement of the merger or acquisition and its resolution date is one of the most important factors when calculation the return of the trade, and thus of great importance for risk arbitrageurs (Kirchner, 2009, p. 80). Samuelson and Rosenthal (1986) found that the market's ability to predict the probability of the outcome of a takeover improves monotonically, as time gets closer to the resolution date.

The variable is defined as the difference between the announcement date and the resolution date, measured in number of days. This data were gathered from the Bloomberg terminal. We expect to find a positive relationship between the number of days until completion and the probability of a successful takeover.

Private Equity

According to Melka and Shabi (2013, p. 60), the inability to secure financing is one of the biggest risks in corporate takeovers. The presence of a private equity firm as a buyer can be of great importance in M&A transactions as they often involve in so-called leveraged buyouts, which often involves a great amount of debt financing (Melka and Shabi, 2013, pp. 239-241). Mitchell and Pulvino (2002) found that there is a negative relationship between a private buyer and the takeover success. However, they do not specify whether that private buyer necessarily must be a private equity firm.

A transaction where the buyer was a private equity firm is a dummy variable that is coded "1" and strategic buyers are coded "0". This data was gathered from the Bloomberg terminal. We expect the absence of a private equity buyer to increase the probability of a successful takeover.

Toehold

Walkling (1985) found that there is a positive relationship between the number of shares that the bidder owns before the takeover attempt and the success rate of the takeover. Walkling is arguing that the reason for this is because the bargaining power of the buyer is directly related to the shares they own. The same positive relation between the number of shares owned by the bidder and the success rate is also found by Branch and Wang (2009). However, they did not found the variable statistically significant.

The data are received from the Bloomberg terminal and defined as the percentage of shares held by the acquirer at the announcement of the transaction. We expect to find a positive relationship between the size of the toehold and the probability of a successful takeover.

4.6 Excluded Predictive Variables

This subsection contains the predictive variables that were not included in our regression model. This is due to lack of sufficient data. In most of our takeovers, there existed no options on the target's shares, making it impossible to calculate the implied volatility. Regarding breakup-fees and advisor's stake in the target company, there was not enough data. We did a trade-off by gathering a bigger sample instead of looking at every variable.

Breakup Fees

It is common that takeover agreements include breakup fees, or termination fees as they are also called. A breakup fee is a fee paid by the target company to the buyer if it suddenly wants to cancel the takeover, it is unsuccessful in getting shareholder approval or if they choose to accept a third-party offer (Kirchner, 2009, p. 53). Another possibility, yet not as common, is a reversed breakup fee, in which the buyer is obliged to pay the target if it decides to cancel the transaction (Kirchner, 2009, p. 53). Officer (2003) manages to empirically show that takeovers with target termination fees have a higher probability of succeeding than takeovers without such contracts.

Implied Volatility in Target Options

One of the variables needed in pricing options using the Black-Scholes-Merton formula is the volatility of the underlying asset. This variable cannot be directly observed and must be estimated from historical data. When an option is traded in the market one can observe the implied volatilities in option prices which is not backward-looking, as the historical volatility data first used when pricing the option, but rather forward-looking as they describe the market's opinion about the future volatility of the underlying asset (Hull, 2015, p. 431). Wang (2009) investigated the differences in implied volatilities in target stock options for successful and failed transactions between the announcement date and the resolution date. In his study, he found that the implied volatilities in the target options diverge over time in cash bids but not in stock bids.

Advisor Stake in Target

Investment banks are usually involved in M&A activity as they act as advisors to the bidder and the target. They conduct valuation, due diligence and provide tactical assistant to their client. Their role, of course, gives the investment bank access to sensitive information about the takeover specifics which possibly could be exploited in the market (Bodnaruk et al., 2009). Bodnaruk et al. (2009) found that when investment banks act as advisors to the buyer and have a stake in the target firm, the probability of a successful takeover is increased. They also found that there is a positive relationship between the stake size and the probability of a successful takeover.

5 Descriptive Statistics and Regression Results

This chapter will present our data output and the results of our study. It will start with the descriptive statistics where the reader will get a good overview of the data used in our study. It will then present the logistic regression as well as the associated discussion.

5.1 Descriptive Statistics

Table 1: Takeover Distribution Over Time

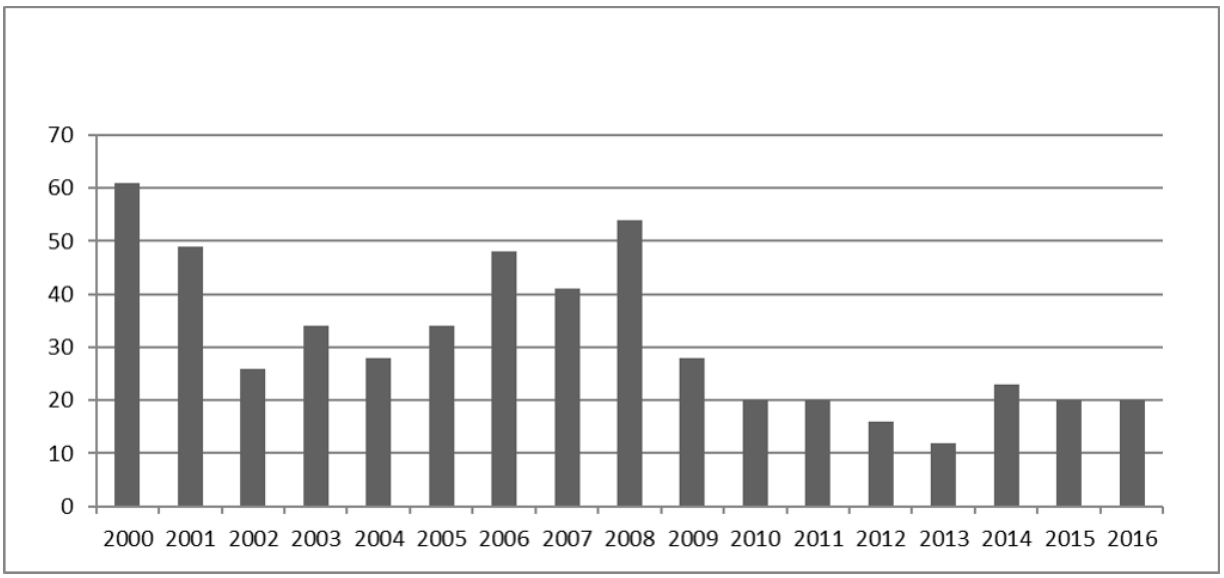
This table presents a comprehensive overview of all the 534 takeovers in our data sample, as well as their distribution over the years. The table presents the total number of deals that occurred every year as well as the number of successful and failed takeovers every year. These numbers are also presented in percentages for each year. The last row presents the total number of deals in our data sample.

Year	Total Takeovers	Successful	Failed	% Successsful	% Failed
2000	61	49	12	80.33%	19.67%
2001	49	40	9	81.63%	18.37%
2002	26	21	5	80.77%	19.23%
2003	34	30	4	88.24%	11.76%
2004	28	24	4	85.71%	14.29%
2005	34	30	4	88.24%	11.76%
2006	48	43	5	89.58%	10.42%
2007	41	31	10	75.61%	24.39%
2008	54	44	10	81.48%	18.52%
2009	28	23	5	82.14%	17.86%
2010	20	17	3	85.00%	15.00%
2011	20	18	2	90.00%	10.00%
2012	16	15	1	93.75%	6.25%
2013	12	10	2	83.33%	16.67%
2014	23	19	4	82.61%	17.39%
2015	20	16	4	80.00%	20.00%
2016	20	14	6	70.00%	30.00%
Overall:	534	444	90	83.15%	16.85%

As can be seen in Table 1 we have identified 534 takeovers, of which 444 (83.15%) succeeded and 90 (16.85%) failed. These numbers can be compared with Branch and Wang (2009) that found only 10.98% of the takeovers in their data to fail over the period 1995-2005 in the U.S. market. This could indicate that takeovers in the Nordic markets, for some reason, has a higher risk of failure. Because of the small number of failed takeovers we see a bias in our data. This could cause some problems in the regression model. However, Branch and Wang (2009) state that a pair-matched sample, where different ratios of failed and successful takeovers are matched together, will falsely lead the arbitrageur to smaller returns compared to the model being used on the whole sample. By looking at Figure 1, we can observe the wave pattern earlier discussed in the theoretical framework. The years following these waves are characterized by lower frequency of takeovers, which could be a cause of increased difficulty to finance the takeover, or that the target company was regarded overvalued.

Figure 1: Takeover Distribution Over Time

This figure presents a bar diagram over our full data sample with number of deals on the y-axis and year on the x-axis.



As can be noted in Table 2, most takeovers are being done with Swedish or Norwegian targets (73.22%), and Iceland only contributing with seven takeovers in total (1.31%). The success rate for the different countries are consistent (Iceland excluded) and should therefore not bias our data in any way.

Table 2: Takeover Distribution Per Country

This table summarizes the target's distribution over the Nordic countries in our data sample. It presents the total number of takeovers per each country, as well as the number of successful and failed takeovers per country.

Country	Observations	Successful	Failed	% of Total Takeovers
Denmark	82	68	14	
	100.00%	82.93%	17.07%	15.36%
Finland	54	44	10	
	100.00%	81.48%	18.52%	10.11%
Iceland	7	7	0	
	100.00%	100.00%	0.00%	1.31%
Norway	191	158	33	
	100.00%	82.72%	17.28%	35.77%
Sweden	200	167	33	
	100.00%	83.50%	16.50%	37.45%

As can be seen in Table 3, the percentage of hostile takeovers, takeovers with competition and private equity takeovers are consistent through all the countries, except for Iceland. We see slightly more private equity takeovers for Danish targets, whereas Finnish, Norwegian and Swedish targets are almost equally less attractive for private equity firms in comparison to Danish targets. Norway has the least number of transactions that were paid with stock (19.37%) and Finland the most (35.19%), once again excluding Iceland from the comparison.

Table 3: Categorical Variables Per Country

This table contains an overview of the distribution of categorical variables for each country.

Country	Hostile	Competition	Toehold	Private Equtiy	Stock
Denmark	1	4	19	9	27
	1.22%	4.88%	23.17%	10.98%	32.93%
Finland	3	0	18	4	19
	5.56%	0.00%	33.33%	7.41%	35.19%
Iceland	1	0	4	0	3
	14.29%	0.00%	57.14%	0.00%	42.86%
Norway	2	8	72	13	37
	1.05%	4.19%	37.70%	6.81%	19.37%
Sweden	7	4	64	15	57
	3.50%	2.00%	32.00%	7.50%	28.50%

In Table 4 one can see that our data sample consists of 2.62% hostile bids, which is slightly less than Branch and Wang (2009), who had 4.65% hostile bids in their data. On the other hand, our data contain 3.00% competing bids, compared with Branch and Wang (2009) who only observed about 1.07%. What is interesting here is that most of the takeovers in our data were paid by cash (73.22%), and only 26.78% stock offers. If we compare this with other studies such as Branch and Wang (2009), we can see that they had almost the reversed distribution of payment method with only about 32.67% cash deals and the rest stock deals (67.33%). It seems like cash is a preferred payment option in the Nordic countries compared to the U.S. Private equity takeovers contributed with 7.68% of the takeovers in our data.

Table 4: Descriptive Statistics: Categorical Variables

This table contains the descriptive statistics of the categorical independent variables for the full data sample.

Friendly Takeovers	Hostile Takeovers	Total
520 (97.38%)	14 (2.62%)	534 (100%)
Competing Bids	Non-competing Bids	Total
16 (3.00%)	518 (97.00%)	534 (100%)
Cash Offer	Stock Offer	Total
391 (73.22%)	143 (26.78%)	534 (100%)
Private Equity	Strategic Buyer	Total
41 (7.68%)	493 (92.32%)	534 (100%)

In Table 5 we can see that the average deal value is 537.57 million dollars with the smallest transaction being 0.78 million dollars and the largest transaction being 9177.77 million dollars. The average bid premium for the deals is 24.51% and the median 16.96%. In 177 of our takeovers in the data sample the acquirer owned shares in the target company prior to the announcement date, with an average ownership of 33.81% and a median of 35.30%. Of all the takeovers in our data sample, the average percentage of shares sought by the acquirer was 86.38% with a median of 100.00%. The average financial leverage of the targets in our data sample is 3.10 with a median of 2.19. The average size of the arbitrage spread is -5.72% with a median of 1.00%. The average number of days from the announcement date until the resolution of the takeover are 122 days, and the shortest period being one day and the longest period running for 1525 days. The target's stock price run-up has an average of -42.59% and a median of -39.32%.

Table 5: Descriptive Statistics: Continuous Variables

This table contains the descriptive statistics for the independent continuous variables in our full data sample. It presents the number of each variable, mean, median, standard deviation, minimum value and maximum value. TTC is an abbreviation for time to completion, and CAR an abbreviation for cumulative abnormal return.

Variable	N	Mean	Median	Std.Dev	Min	Max
Target Size (million USD)	534	537.57	157.12	1083.82	0.78	9177.77
Premium One Week	534	24.51%	16.96%	58.76%	-99.80%	450.89%
Percentage Sought	534	86.38%	100.00%	19.57%	40.00%	100.00%
Toehold *	177	33.81%	35.30%	16.28%	2.00%	60.00%
Leverage	534	3.10	2.19	3.90	0.00	33.10
Arbitrage Spread	534	-5.72%	1.00%	31.62%	-100.00%	144.11%
TTC (days)	534	122	91	115	1	1525
CAR	534	-42.59%	-39.32%	30.88%	-196.47%	42.51%

*Bidders own target shares prior to the announcement in 177 of the deals in our full data sample.

5.2 Results from Logistic Regression

This subsection discusses the selection of independent variables based upon the Pearson correlation measure between the variables, as well as the Variance Inflation Factor (VIF). The latter is presented in Table 6 and the former in Appendix I. After that, we use a stepwise regression algorithm to effectively choose appropriate variables that minimize the information loss. We present the best fitting model and compare it to a model which incorporates all independent variables. We later discuss each estimated predictor and its coefficient and compare to previous research.

All correlations that have an absolute value exceeding 0.80 might be subject to multicollinearity (Brooks, 2014, p.218). Based on the Pearson correlation measure, we see that there is a nearly perfect negative correlation between the two variables percentage sought and toehold.

Based upon the Variance Inflation Factor we can assess that the independent variables percentage sought and toehold are subject to multicollinearity. Cohen et al. (2003) point out a rule of thumb regarding assessing the magnitude of multicollinearity, if the VIF value is greater than 10.00, one could suspect multicollinearity. Branch and Wang (2003) also used this rule of thumb to assess the multicollinearity in their data sample. In our case, percentage sought yields a value of 14.20 and toehold 14.06. This indicates that the standard error is likely to be 3.77 times higher for the variable percentage sought and 3.75 times higher for the variable toehold. To assess this problem appropriately, we need to see if there exists inconsistency in their standard errors. One possible explanation of this multicollinearity is the fundamental relationship between percentage sought and toehold. Because existing ownership will be taken into consideration when the acquirer is bidding on the target company to retrieve the majority of the shares and the control of the company.

Table 6: Variance Inflation Factor (VIF)

This table presents the VIF for each independent variable, which assess multicollinearity. TTC is an abbreviation for time to completion, and CAR an abbreviation for cumulative abnormal return.

Target Size	Premium One Week	Payment	Attitude	Percentage Sought	Toehold
1.1077	1.2173	1.2608	1.1427	14.1990	14.0621
Competing Bids	Leverage	Private Equity	Arbitrage Spread	TTC	CAR
1.0656	1.0458	1.1247	1.2560	1.1471	1.0620

Table 7: Model Selection

This table presents the stepwise regression that we used to find the best fitting logistic regression model. We used a forward selection process based upon the Akaike Information Criterion (AIC) to select the continuous variables. The forward selection process is built upon five selection steps with the purpose to minimize the information loss due to model selection, starting with a model with only the intercept. To address the goodness-of-fit regarding each suggested model, we have used a log-likelihood value, pseudo R^2 McFadden and adj. pseudo R^2 McFadden.

Continuous Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Intercept	1.596	-2.2879	-1.3549	-0.1942	4.5576
Time To Completion		0.8985	0.9644	0.9965	1.0778
Target Size			-0.2346	-0.209	-0.2128
Percentage Sought				-1.6266	-6.7322
Toehold					-5.7692
Leverage					
Arbitrage Spread					
Premium One Week					
Cumulative Abnormal Return					
AIC	486.4	445.5	437.8	434.3	429.5
Log-likelihood Value	n/a	-220.73 ***	-215.91***	-213.15***	-209.74***
Pseudo R^2: McFadden	0	0.0886	0.1085	0.1199	0.1340
Adj. Pseudo R^2: McFadden	0	0.0763	0.0920	0.0993	0.1093

***,**,* indicate statistical significance at the 1%, 5% and 10% level, respectively.

In Table 7 we can see that AIC is continuously decreasing until Model (5) where the minimum of 429.5 is observed. The usage of a stepwise regression is in line with previous studies (See Branch and Yang, 2003), although they set a p-value equal to 0.15 as their threshold for including the variable or not. By assessing the log-likelihood value, we can see that it decreases through the selection process. All models (excluding Model (1), as the log-likelihood value is not applicable), are statistically significant at the 1.0% level, indicating that the model's goodness-of-fit becomes better.

In order to assess the impact of the multicollinearity in the independent variables percentage sought and toehold, we have tried to exclude one or both variables without improving the log-likelihood value, neither the AIC. Thus, we will keep both variables in our final model. Besides that, we observe the pseudo R^2 McFadden to increase as more predictors are added. Therefore, it is crucial to assess the Adj. R^2 McFadden measure. We see that the measure increase through the selection process, adjusted for an addition of predictors, which indicates a better goodness-of-fit.

Table 8: Logistic Regression Model: All Independent Variables

This table presents the estimated coefficients for a model that includes all the independent variables. The table presents our expected effect, the estimated coefficients and their standard errors, the odds-ratio as well as the significance level for each variable.

Variable	Expected Sign	Coefficients	Std. Error	OR	
Intercept		1.5098	2.9594	4.5260	
Time To Completion	+	1.1488	0.1733	3.1545	***
Target Size	-	-0.1899	0.0827	0.8270	**
Percentage Sought	-	-6.4652	2.7009	0.0016	**
Toehold	+	-5.8062	2.7559	0.0030	**
Leverage	-	0.0054	0.0320	1.0054	
Arbitrage Spread	-	0.2359	0.4414	1.2661	
Premium One Week	+	0.0045	0.2331	1.0045	
Cumulative Abnormal Return	+	-0.3908	0.4454	1.5611	
Attitude	+	2.3029	0.6595	10.0027	***
Private Equity	-	-1.3866	0.7197	0.2499	*
Competing Bids	+	1.0754	0.5844	2.9312	*
Payment	+	0.4213	0.3129	1.5240	
AIC		425.25			
Log-likelihood Value		-199.37	***		
Pseudo R_2 McFadden		0.1757			
Adj. Pseudo R_2 McFadden		0.1191			
Correct Predictions		44.20%			

***,**,* indicate statistical significance at the 1%, 5% and 10% level, respectively.

By assessing the AIC measure in Table 8, we can see that adding additional categorical variables decrease the measure and likewise increase the adjusted Pseudo R^2 McFadden measure. The model has a log-likelihood value that is below the threshold of 1.0%, which indicates a good fit compared to the null model with only the intercept. By assessing the accuracy of the model, it has been used on a testing data set, consisting of data points unique from the training set. The model predicts the outcome with 44.20% accuracy.

Table 9: Logistic Regression Model: Selected Independent Variables

This table presents our best fitting model, based upon the model selection presented in table 7. The table presents our expected effect, the estimated coefficients and their standard errors, the odds-ratio as well as the significance level for each variable.

Variable	Expected Sign	Coefficients	Std. Error	OR	
Intercept		1.5604	2.9103	4.7609	
Time To Completion	+	1.1401	0.1721	3.1271	***
Target Size	-	-0.1919	0.0821	0.8253	**
Percentage Sought	-	-6.2701	2.6593	0.0019	**
Toehold	+	-5.5713	2.7153	0.0038	**
Attitude	+	2.2471	0.6434	9.4603	***
Private Equity	-	-1.3564	0.7136	0.2576	*
Competing Bids	+	1.0371	0.5817	2.8210	*
Payment	+	0.4531	0.2968	1.5732	
AIC		418.4			
Log-likelihood Value		-200.00	***		
Pseudo R_2: McFadden		0.1734			
Adj. Pseudo R_2: McFadden		0.1330			
Correct Predictions		71.38%			

***,**,* indicate statistical significance at the 1%, 5% and 10% level, respectively.

Comparing the best fitting model (presented in Table 9) with the full model, we see that the best fitting model has a lower AIC value, which indicates that the information loss is smaller than in the full model. This is the cause of the forward selection process as well as the information gained from the categorical variables. The model also shows an increase in the Adj. Pseudo R^2 McFadden measure from 0.1191 to 0.1330. We also see that the model is a better fit to the data compared to the null model, where a statistical significance is shown below 1.0%. The model also shows increased accuracy compared to the full model, as the correct predictions have increased from 44.20% to 71.38%.

The log-likelihood value for the best fitting model is lower than the log-likelihood value of the full model, which could indicate inferiority for the best fitting model, contrary all other measures. By assessing a likelihood-ratio test between the two models, we can see that this inferiority is not statistical significant on any level. In Table 10 the output from the R code is displayed. We can observe the insignificance by looking at the p-value, which is 85.71%.

Table 10: Likelihood-ratio Test

This table presents a likelihood-ratio test between the full model and our best fitting model.

Model	# Degrees of Freedom	Likelihood Ratio	Chisq	Pr()
Full Model	13	-199.37		
Best Fitting Model	9	-200	1.2658	85.71%

Therefore, we suggest that the best fitting model is superior to the full model, since the goodness-of-fit is in general better. It must be commented that the Adj. Pseudo R^2 McFadden indicates that our model does not fit our data well. This could be the cause of discrepancies in the true probability function and our used probability function. In the following sections, we will discuss the estimated coefficients of the variables included in our model.

The most researched predictive variable is the target attitude and its relationship to the outcome of the takeover. In each model, the attitude has shown to have a significant impact on the outcome. Throughout the selection process, this variable has shown high significance, consistently at the 1.0% level. The sign of the predictor is positive, which is in line with our expectation that friendly offers are more likely to succeed than hostile. This positive relationship has been proved by previous studies (See Branch and Yang (2003); Branch and Wang (2009); Hoffmeister and Dyl (1981)).

Looking at the odds-ratio, we can see that friendly takeovers are 9.46 times more likely to succeed than hostile takeovers. This odds-ratio is generally too extreme for proper interpretation. This could be the cause of bias in our data since we only observed 15 hostile takeovers. Our second most significant variable is the time to completion, which is shown to have a strong positive relationship to the outcome of a takeover, as it is significant at the 1.0% level in the final model. This result is in line with our expectation. Looking at the odds-ratio, we expect an increase of 217.53% per day elapsed in the odds of a successful takeover. This is in line with the result from Samuelson and Rosenthal (1986) where the market's ability to predict the probability of a takeover outcome improves monotonically.

Three variables are found to be significant at the 5.0% level in the best fitting model: the target size, percentage of shares sought and toehold. All these variables are consistently significant at the 5.0% level throughout the variable selection process. Target size is negatively related to the success rate of the takeover, which is in line with our expectation and previous studies (See Branch and Yang (2003); Branch and Wang (2009); Hoffmeister and Dyl (1981); Cotter et al., (1997); Schwert (2000)). Looking at the odds-ratio, we see that for every increase of one million USD in target size the odds of a successful outcome decreases by 17.47%.

Percentage of shares sought and toehold are also proven to have a significant impact on the outcome of the takeover, even though they suffer from multicollinearity. Our results for toehold is not in line with our expectation or previous literature (See Walkling (1985)), as our regression gives a negative relationship between the size of toehold and the probability of a successful takeover. The negative relationship between the percentage of shares sought and the success rate of a takeover is in line with our expectation and previous literature (See Branch and Yang (2003)). By assessing the odds-ratio of the variable percentage of shares sough, we can see that it is close to zero, which should be interpreted as a decrease of 99.81% in the odds per additional percentage sought.

Looking at the odds-ratio of the variable toehold, we can see that one percent increase in ownership prior to the takeover decreases the odds of a successful outcome by 99.62%. Notice that this variable has an upper bound of 60.00%, since we made that restriction in our data selection.

At the 10.0% significance level, we observe the variables competing bids and private equity. Interesting here is that competing bids did not gain a higher significance level as previous studies (See Walkling (1985) and Branch and Wang (2009)) have found that competing bids, together with attitude, is one of the strongest predictors. There could be some possible explanations to this, for example that we have a very small number of transactions with competing bids in our sample, which could cause bias in our results. Another possible explanation could be that competing bids do not have an as strong impact on the takeover outcome in the Nordic markets as it have in other markets.

Regardless of significance level, the relationship between the variable and the takeover outcome is in line with our expectation as well as previous literature. Looking at the odds-ratio, the absence of competing bids will increase the odds of a successful takeover with 182.10% relative to the odds of success when there are competing bids.

Our results show that the presence of a private equity firm as the buyer will decrease the probability of a successful takeover. This is in line with our expectation. Mitchell and Pulvino (2002) have previously shown a negative relationship between a private buyer and the probability of a successful takeover. We do now show that this relationship still holds when that private buyer specifically is a private equity firm. From the odds-ratio, we can read that the odds of a successful takeover will decrease with 74.24% when there is a private equity firm as the buyer, compared to the odds when there is a strategic buyer.

The last variable that our best fitting model is including is the payment type. The regression shows a positive relationship between pure cash payments and the probability of a successful takeover. This is in line with our expectation and previous literature (See Branch and Wang (2009)). However, this variable is not statistically significant at 1.0%, 5.0% nor 10.0%. A possible explanation to this can be the reversed frequency distribution of cash compared to stock payment in the Nordic markets compared to the data in previous studies (See Branch and Yang (2003)).

Variables that was neither proven significant or included in our best-fitting model were bid premium, target's stock price run-up, arbitrage spread and leverage. Neither was the effect of these variables in line with our expectation (bid premium excluded).

Our model predicted target leverage and the arbitrage spread to have a positive impact on the probability of a successful takeover. These findings contradict our expectations as well as previous research (See Samuelson and Rosenthal (1986); Brown and Raymond (1986); Branch and Wang (2009); Raad and Ryan (1995); Branch and Yang (2003); Schwert (2000)).

Our model did also predict the target's stock price run-up to have a negative impact on the probability of a successful takeover. This does not only contradict our expectation, but also the findings of Branch and Wang (2009), who found the target's stock price run-up to have a significant positive effect on the takeover outcome.

6 Conclusion

The purpose of this thesis has been to investigate predictive variables of the outcome in corporate takeovers in the Nordic markets by creating a prediction model using a logistic regression.

Our data sample of 534 corporate takeovers in the Nordic markets between January 1st, 2000 and December 31th, 2016 has proven that some variables have a significant impact on the takeover outcome. We have concluded that our best fitting prediction model contains the variables: time to completion, target size, percentage sought, toehold, target attitude, private equity, competing bids, and payment method. Hence, we can conclude that many of the variables that previously been proven significant outside the Nordic markets when predicting a takeover outcome are applicable in the Nordic markets as well. However, we cannot find the arbitrage spread, target leverage, bid premium or the target's stock price run-up to have a significant impact on the takeover outcome in the Nordic markets, even though previous studies have found them to have a significant impact on the takeover outcome in other markets.

Our results cannot only be of great knowledge to risk arbitrageurs active in the Nordic markets, but also to senior management of companies that are looking for a suitable acquisition in the Nordic markets. We also believe that the time range of our data sample will contribute to the robustness of our findings as well as strengthen previous findings that are in line with ours.

6.1 Further Studies

Our first suggestion for future research would be to continue our study on a more country-specific basis within the Nordic markets. However, the number of transactions would be reduced significantly if such an approach was taken, which could bias the results. In case one took this approach, the research could be tailored in a more country-specific manner and could, for example, include variables such as country specific antitrust laws.

The target attitude has been shown in this thesis, and by previous studies (See Branch and Yang (2003); Branch and Wang (2009); Hoffmeister and Dyl (1981)), to be one of the most significant variables when predicting a takeover outcome. Melka and Shabi (2013, p. 63) define a hostile takeover as a situation when the management or the board of the target company reject the approach from the potential acquirer. However, in the end, it is up to the shareholders of the target company to decide whether they want to sell their shares or not. Hence, it would be interesting to investigate hostile takeovers further, and especially the ownership structure in these takeovers (e.g. insider ownership). One problem with this study, at least in the Nordic markets, would be the scarce number of hostile takeovers (only 2.62% in our sample).

Another interesting approach would be to create the prediction model using artificial neural network instead of a logistic regression model. Artificial neural network models have been shown by Branch et al. (2008) to outperform the logistic regression when predicting failed takeovers, and on par when predicting successful takeovers. It would be interesting to see how such a model would perform in the Nordic markets, in the same manner that we have tested the logistic regression in this thesis.

It would also be interesting to test the performance of our model in the Nordic markets to see if it can generate abnormal returns by implementing the model in a risk arbitrage strategy.

7 References

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Appendix I: Correlation Matrix

Table 11: Pearson Correlation Matrix

	DV	POW	PAY	ATT	PS	TH	CB	LEV	PE	AS	TTC	CAR
DV	1,0000	0,0374	-0,0452	-0,0879	0,1667	-0,1419	-0,1147	0,0989	0,0609	-0,0270	0,1101	0,0459
POW	0,0374	1,0000	0,1487	-0,0586	0,1033	-0,0774	0,0200	-0,0283	0,0252	0,3920	0,0183	0,0177
PAY	-0,0452	0,1487	1,0000	-0,0813	-0,2377	0,2091	-0,1025	-0,0322	0,1682	0,2609	-0,1000	0,0604
ATT	-0,0879	-0,0586	-0,0813	1,0000	-0,0575	0,0394	-0,0288	-0,0152	-0,0847	-0,0521	-0,0461	0,0314
PS	0,1667	0,1033	-0,2377	-0,0575	1,0000	-0,9071	-0,0129	0,0183	-0,0050	0,0251	0,0523	0,0606
TH	-0,1419	-0,0774	0,2091	0,0394	-0,9071	1,0000	0,0152	-0,0027	-0,0236	-0,0162	0,0203	-0,0833
CB	-0,1147	0,0200	-0,1025	-0,0288	-0,0129	0,0152	1,0000	0,0228	0,0507	-0,0572	0,0447	0,0283
LEV	0,0989	-0,0283	-0,0322	-0,0152	0,0183	-0,0027	0,0228	1,0000	-0,0162	-0,0275	-0,0205	-0,1490
PE	0,0609	0,0252	0,1682	-0,0847	-0,0050	-0,0236	0,0507	-0,0162	1,0000	0,0769	-0,0061	0,0470
AS	-0,0270	0,3920	0,2609	-0,0521	0,0251	-0,0162	-0,0572	-0,0275	0,0769	1,0000	-0,0077	0,0401
TTC	0,1101	0,0183	-0,1000	-0,0461	0,0523	0,0203	0,0447	-0,0205	-0,0061	-0,0077	1,0000	0,0175
CAR	0,0459	0,0177	0,0604	0,0314	0,0606	-0,0833	0,0283	-0,1490	0,0470	0,0401	0,0175	1,0000

TS = Target Size, POW = Premium One Week, PAY = Payment, ATT = Attitude, PS = Percentage Sought, TH = Toehold, CB = Competing Bids, LEV = Leverage, PE = Private Equity, AS = Arbitrage Spread, TTC = Time To Completion, CAR = Cumulative Abnormal Returns

Appendix II: R Code

```
library(xlsx)
library(lmtest)
library(pscl)
library(BaylorEdPsych)

#Load the data from the excel-file.
df.2 <- read.xlsx("logisticregression.xlsx", sheetIndex = 1, header = TRUE)

#Define the  null model
null=glm(Outcome~1, family = binomial, data = df.2)

#Define the full model
full=glm(Outcome~ TTC + Deal.value + Percent.Sought + Toehold + CAR +
Arbitrage.Spread + Leverage + Premium1week, family = binomial, data = df.2)

#Perform a foward selection process
forward.model <-step(null, scope=list(lower=null, upper=full),
direction="forward")

#Prints out the most essential information regarding the selected model
summary(forward.model)

#Initial model (null)
null.model<-glm(Outcome~1, family = binomial, data = df.2)
null.model
pR2(null.model)

in#Add one variable
model.1 <- glm(Outcome ~ TTC, data = df.2, family = binomial)
model.1
PseudoR2(model.1)
pR2(model.1)
lrtest(null,model.1)

#Two variables
model.2 <- glm(Outcome ~ TTC + Deal.value, data = df.2, family = binomial)
model.2
```

```
PseudoR2(model.2)
pR2(model.2)
lrtest(null, model.2)

#Three variables
model.3 <- glm(Outcome ~ TTC + Deal.value + Percent.Sought, data = df.2,
family = binomial)
model.3
PseudoR2(model.3)
pR2(model.3)
lrtest(null, model.3)

#Four variables
model.4 <- glm(Outcome ~ TTC + Deal.value + Percent.Sought + Toehold,
data = df.2, family = binomial)
model.4
PseudoR2(model.4)
pR2(model.4)
lrtest(null, model.4)

cor(df.2, use="complete.obs", method="pearson")

#Selected model; countinous variabels as well as binary variables
selected.model <- glm(Outcome ~ TTC + Deal.value + Percent.Sought + Toehold
+ Attitude + Private.Equity + Competing.bids + Payment,
 data = df.2, family = binomial)
summary(selected.model)
PseudoR2(selected.model)
lrtest(null,selected.model)
pR2(selected.model)

exp(coefficients(selected.model))

#Full model; including all variables
full.model <- glm(Outcome ~., data = df.2, family = binomial)
summary(full.model)
PseudoR2(full.model)
lrtest(null, full.model)
pR2(full.model)
```

```
exp(coefficients(full.model))

#Classification Rate Selection Model
library(dplyr)
df.testing <- read.xlsx("dataframe_regression.xlsx", sheetIndex = 2, header = TRUE)

df.testing$model_prob <- predict(selected.model, newdata = df.testing,
type = "response")

Test <- df.testing %>% mutate(model_pred = 1*(model_prob > 0.51) + 0)

Test <- Test %>% mutate(accurate = 1*(model_pred == Outcome))
sum(Test$accurate)/nrow(Test)

#Classification Rate Full Model
df.testing$model_prob.2 <- predict(full.model, newdata = df.testing,
type = "response")
Test.2 <- df.testing %>% mutate(model_pred.2 = 1*(model_prob.2 > 0.51) + 0)

Test.2 <- Test.2 %>% mutate(accurate = 1*(model_pred.2 == Outcome))
sum(Test.2$accurate)/nrow(Test.2)
```