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Predicting Norwegian Takeover Targets

An Empirical Analysis of the Norwegian M&A Market

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“It is difficult, if not impossible, for the market to predict future targets.”

(Jensen & Ruback, 1983)

Abstract

The prediction of takeover targets has been covered in several studies. However, it tends to be the same major stock exchanges that are subject to analysis. Based on 153 Norwegian public targets from 1995 to 2012, we develop the first takeover prediction model for the Oslo Stock Exchange. We find evidence for the propositions that firms with underperforming management and poor liquidity are more likely to become targets. To test the practical application of the model, we use it as basis for investment strategies. As our analysis on takeover announcement returns show that Norwegian firms experience a cumulative average abnormal return of 14.7% over a [-50,50] window, a successful investment strategy could be highly profitable. Thus, we use the takeover prediction model on Norwegian market data from 2013 to 2016 to classify firms as targets and non-targets. The model is to some degree successful, as it assigns takeover probability of 36.3% among actual targets compared to 27.6% among non-targets. However, by investing in predicted targets and replicating the portfolio strategies that Palepu (1986) and Powell (2001) uses, we find insignificant market-adjusted return of 1.8% and 0.9%, respectively. Hence, the results suggest that the takeover prediction model fails to form the basis for successful investment strategies.

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Preface

This dissertation was written as a part of our Master of Science in Economics and Business Administration at the Norwegian School of Economics (NHH). Several individuals have contributed academically with their valuable input and discussions on different aspects of this thesis.

Firstly, we would like to extend our gratitude to our supervisor, Karin S. Thorburn, for her prolific counseling on both the choice of topic as well as continuous input and constructive criticism throughout writing this thesis. Her extensive knowledge in the field of Corporate Finance, M&A in particular, have decidedly improved the quality of the thesis. We would also like to thank the SNF research environment for access to their datasets on ownership structure among Norwegian public companies. Further, we would like to thank Aksel Mjøs who kindly provided additional historical data on ownership structure allowing us to cover a lengthened period of time.

Finally, we would like to thank the professors at the finance faculty at NHH for thought-provoking ideas and the professors at the department of economics for sharing their profound knowledge of statistical tools used in our thesis.

Bergen, June 2018

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1 Introduction

Corporate takeovers are often attractive for target shareholders as it involves significant premiums. Empirical evidence shows that target shareholders on average earn cumulative abnormal return (CAR) of 23.8% from 20 days prior to the announcement until the deal closes (Andrade, et al., 2001). This represents an opportunity for investors to earn outstanding returns if they correctly predict acquisition targets. Based on publicly available information, several earlier studies have attempted to develop takeover prediction models and test their ability to form the basis for successful investment strategies.

Palepu (1986) is the most celebrated empirical study on takeover prediction. Based on Jensen and Ruback's (1983) proposition that the market for corporate control is an arena where managers compete for the rights to control corporate resources, he develops the takeover prediction model. As takeovers, in some cases, represent a disciplinary action against the underperforming management of a company, Palepu (1986) uses financial metrics to differentiate between target and non-target firms. In total, he outlines six hypotheses and applies logistic regression to sign each firm a takeover probability. Numerous empirical studies build upon Palepu's (1986) study.[1] In newer literature, additional variables, such as liquidity, ownership structure and commodity prices, are added to control for new hypotheses that can influence takeover likelihood.

Palepu (1986) also tests the takeover prediction models' ability to form the basis for successful investment strategies. By investing in all companies that were classified as targets and with an investment horizon of 250 trading days, he finds an insignificant CAR of -1.6%. Brar, Giamouridis and Liodakis (2009) use a different investment strategy by constructing a portfolio of only upper 10% takeover probability firms. They find a significant CAR of 8.5% in a one-year investment period with monthly rebalancing. Thus, previous studies report contradictory results on whether it is possible to earn significant abnormal returns by investing in future targets predicted by the model.

Following previous empirical studies, our main research question is whether it is possible to predict takeover targets at Oslo Stock Exchange (OSE) and invest in these predicted targets to

[1] See Ambrose and Megginson (1992), Barnes (1999), Powell (2001), Cremers, Nair and John (2009), among others.

earn a positive CAR. We perform three analyses to investigate these objectives. First, we examine whether target shareholders at OSE historically experience significant CAR in takeovers. As this is an underlying assumption in developing a takeover prediction model and investment strategies, we find the analysis important for our paper. Moreover, the analysis gives us insight into which industries experience highest premiums and should be included in the portfolios. Second, based on logistic regression, we develop a takeover prediction model by using data from 153 Norwegian publicly listed targets and 2,087 non-targets from 1994 to 2012. Third and finally, we apply the developed takeover prediction model to predict takeover targets at OSE from 2013 to 2016. Based on the model, we invest in portfolios consisting of predicted takeover targets to test whether it is possible to earn a positive CAR.

Thus, our thesis contributes to previous literature in several ways. It determines whether Eckbo and Solibakke's (1991) findings of significant and positive CAR for Norwegian target shareholders in successful acquisitions still holds. Our study extends previous empirical literature, as it is the first time a takeover prediction model for the Norwegian market is developed. Moreover, as OSE is characterized by concentrated ownership and is less liquid compared to the more frequently analyzed markets of the US and UK, OSE might be less efficient.[2] This could increase the odds of successfully being able to generate positive CAR by investing in predicted targets. In addition to hypotheses suggested by previous research (see, e.g. Palepu, 1986), we also control for factors such as oil price, interest rate and governing party in Norway. Consequently, our analysis gives a broader and deeper insight into the market efficiency with regards to takeovers and expected takeovers in the Norwegian market.

This paper is organized as follows: Section 2 presents the empirical evidence from existing literature. Section 3 provides the hypotheses on takeover announcement return and takeover prediction. Section 4 describes the data used in the paper. Section 5 presents the methodology used when conducting our analyses. Section 6 provides our empirical results. Section 7 concludes the paper and adds suggestion for further research.

[2] According to Døskeland and Mjøs (2008), the Norwegian market is characterized by concentrated ownership structure.

2 Literature Review

In this section, we review the relevant studies on takeover gains, takeover prediction models and their ability to generate abnormal returns. As the purpose of this paper is twofold, with the main objectives being prediction of takeover targets and the models' ability to form the basis for successful investment strategies, we will focus on literature related to these subjects. However, an underlying assumption in developing takeover prediction models and successful investment strategies is that target shareholders earn significant abnormal returns in takeover processes. Thus, we will first present empirical literature on takeover announcement returns. This is followed by empirical examination of takeover prediction models.

2.1 Empirical Evidence on Takeover Announcement Returns

Historically, takeovers often include a significant premium to target shareholders. A wide set of papers provide empirical evidence that target shareholders earn abnormal returns within two months of the first bid. Table 1 offers a selected list of prominent studies that reports CAR, which is the sum of all abnormal returns within an event window, from the US, Europe and Norway.

Table 1 - Takeover returns for target shareholders
This table gives an overview of empirical studies on takeover announcement returns earned by target shareholders in acquisitions.

Study	Cumulative Abnormal Returns	Sample Period	Event Window (Trading Days)	Additional Information
Langetieg (1978)	+10.6%***	1929-1969	(-126,0)	-Observations (n) 149 -US Deals
Jarell & Poulsen (1989)	+28.9%***	1963-1986	(-20,+10)	-Observations (n) 526 -US Deals
Eckbo & Solibakke (1991)	+3.9%** +8.0%**	1983-1989	(-1,0) (-10,0)	-Observations (n) 240 -Norwegian Deals
Schwert (1996)	+30.1%**	1975-1991	(-42,+126)	-Observations (n) 1174 -US Deals
Andrade, Mitchell & Stafford (2001)	+16.0%*** +23.8%***	1973-1998	(-1,+1) (-20, Close)	-Observations (n) 3688 -US Deals

Goergen & Renneboog (2004)	+21.6%*** +29.3%***	1993-2000	(-60,+60)	-Observations (n) 136 -European Deals -UK Deals: 70

** and *** shows statistical significance at the 5% and 1% significance level, respectively

Jensen and Ruback (1983) review thirteen studies on target firm abnormal stock price returns during takeovers. They find that target shareholders receive statistically significant abnormal returns of 20% and 30% in successful mergers and tender offers, respectively. Focusing on individual studies, Langetieg (1978) finds that US target firms experience a positive stock price change of 10.6% from 126 days before to the day of the deal announcement. Moreover, Schwert (1996) shows a similar result for the period 1975-1991. He examines an event window from 42 days prior to 126 days after the deal announcement and finds that target shareholders earn abnormal returns of 30.1% in successful deals. In an extensive study, including 3,688 successful deals from 1973 to 1998, Andrade, Mitchell and Stafford (2001) find that target shareholders earn significant abnormal returns of 16% from one day prior to one day after the deal announcement. They also extend the event window to 20 days prior to the announcement until the deal closes, more specifically an average deal length of 142 days, and find that target shareholders receive significant abnormal returns of 23.8% during the period.

Goergen and Renneboog (2004) extend previous studies of takeover gains by shifting the focus from the US market to Continental Europe. They argue that the UK market is more like the US compared to the rest of Europe. They highlight the difference between listed companies on the London Stock Exchange, where 85% are widely held, to the smaller European markets, where the number of listed firms are much smaller and ownership tends to be much more concentrated. Indeed, UK targets generate significantly larger returns than their counterparts from the rest of Europe. While UK target shareholders experience abnormal returns of 29.3% in an event window from 60 days prior to 60 days after deal announcement, Continental European targets experience relatively lower returns at 21.7% in the same event window. Goergen and Renneboog (2004) argue that this can to some extent be explained by the more established market for corporate control and the higher fraction of hostile takeovers in the UK.

We find Goergen and Renneboog's (2004) findings interesting, as Norway is part of Continental Europe. Døskeland and Mjøs (2008) show that the Norwegian market is characterized by concentrated ownership, which is in line with Goergen and Renneboog's (2004) expectations. Thus, we should expect lower target shareholder returns in Norway compared to the US and the UK. This is confirmed by Eckbo and Solibakke (1991), who find that target shareholders on Oslo Stock Exchange experience abnormal returns of 8.0% from 10 days prior to the deal announcement. We also compute cumulative abnormal returns for our sample to get an updated estimate of takeover premiums in the Norwegian market.

Moreover, there are various firm-specific factors that influence target shareholders´ abnormal returns. Melicher and Nielsen (1978) find that target size has a positive effect on cumulative abnormal returns in takeover processes. Eckbo (2009) finds that targets with a book-to-market value higher than the industry median have significantly higher gains. Walking and Edmister (1985) report similar results as Eckbo (2009), and in addition that lower target leverage results in higher premiums.

2.2 Empirical Evidence on Prediction of Takeover Targets

We divide our literature review of takeover prediction models and their ability to generate abnormal returns into two sections. In the first section, we conduct a review of the most celebrated study, Palepu (1986), in the takeover prediction model literature. In the second section, we examine related empirical studies, which propose additional characteristics of takeover targets to take into account and other investment strategies than the one Palepu (1986) apply.

2.2.1 Theoretical and Empirical Evidence from Palepu (1986)

Palepu (1986) has been widely adapted by later studies seeking to develop takeover prediction models. His study contains three essential sections that we find important to cover. First, Palepu (1986) outlines six characteristics of takeover targets that are the basis for estimating a firm's acquisition likelihood. Second, he presents three methodological flaws with previous takeover prediction studies and proposes the use of logistic regression. Third, Palepu (1986) analyzes whether the developed takeover prediction model is able to form the basis for successful investment strategies.

Palepu (1986) proposes the use of nine independent variables to estimate the takeover likelihood of a firm. These nine variables are based on six hypotheses; inefficient management, small firm size, mismatch between growth and financial resources, low asset undervaluation and low price-earnings ratio. We find it relevant to review these characteristics of takeover targets, as we include these in our attempt to differentiate between Norwegian targets and non-targets.

First, the inefficient management proposition is based on Manne's (1965) theory of the market for corporate control and Jensen and Ruback's (1983) management competition model. They argue that underperforming management increases the probability of a company being subject to a takeover due to the potential managerial synergies for bidders. Palepu (1986) incorporates this in the takeover prediction model by using share price abnormal return and return on equity as proxies for management quality.

Second, Palepu (1986) argues that the takeover likelihood decreases with the size of the firm. This implies there is a negative correlation between takeover probability and firm size, and smaller firms are relatively more likely to become targets. Palepu (1986) argues that transaction costs increases with the size of the target. These costs could include takeover defense costs or post-merger integrations costs that directly reduce the synergies and negatively affect the initial deal motivation. Thus, due to increasing firm size, the number of potential bidders decreases and firms are less likely to become targets. Palepu (1986) uses net book assets to test for this hypothesis.

Third, growth-resource mismatch examines the relationship between the company's growth opportunities and current financial resources. First, Palepu (1986) suggests that low-growth, resource-rich firms are more likely to be targets as they are indirectly underperforming based on the assets at their disposal. Second, based on Myers and Majluf (1984), Palepu (1986) argues that high-growth, resource-poor firms are also more likely to be acquired. He argues that these firms offer growth expansion for bidders at a relatively low price due to few target assets to acquire. Palepu (1986) tests this hypothesis by including a growth-resource imbalance dummy variable in his takeover prediction model.

Fourth, Palepu (1986) suggests the asset undervaluation hypothesis. He argues that companies with low market value relative to the book value of their assets are more likely to become takeover targets. That is, firms with low market-to-book (MTB) ratios are relatively more likely to be targeted than companies with high MTB, as companies with low MTB are perceived to be undervalued.

Fifth, Palepu (1986) proposes that firms with high price-earnings (P/E) ratios acquire firms with low P/E ratios due to the belief that the market will revalue the acquired earnings at the higher P/E multiple, resulting in an instant value gain. Thus, acquiring companies can increase their market value by targeting low P/E firms.

Sixth, Palepu (1969) controls for industry disturbance in the takeover prediction model. The theoretical background is based on Gort (1969) and Mitchell and Mulherin (1996), who suggest that industry disturbance triggers takeovers. They argue that economic shocks influence merger activity within an industry. These economic shocks could include technological, legal and financial innovations that change the competitive landscape for firms and force them to adjust their strategy. Palepu (1986) incorporates the industry disturbance hypothesis by including a dummy variable, which equals one if there was a takeover in the same industry in the previous year. He applies the company's standard industrial classification (SIC) code to distinguish between industries. Palepu (1986) argues that the recent history of acquisitions in an industry reflects the takeover likelihood of a firm, as the theory suggests that takeovers cluster by industry.

The second section in Palepu (1986) that we find interesting to review covers the methodology, as this forms the ground for our methodology to develop a takeover prediction model. Empirical studies prior to Palepu (1986) claim to construct takeover prediction models that have explanatory power of 60 to 90 percent. However, Palepu (1986) argues that earlier studies have three methodological flaws, which make the accuracy of their model predictions unreliable.[3] First, the use of non-random, equal-size samples for targets and non-targets in model estimation leads to biased results. Second, the use of equal-size samples in prediction tests leads to misleading estimates that fail to explain the takeover prediction models' accuracy. Third, the use of arbitrary cut-off probabilities in prediction tests make the estimates difficult to interpret. Indeed, he criticizes the use of cut-off probabilities of 50% to derive the classification of targets and non-targets.

[3] See Simkowitz and Monroe (1971), Stevens (1971), Belkoui (1978), Dietrich and Sorensen (1984), among others for empirical studies prior to Palepu (1986).

To correct for these flaws, he uses a logistic regression method to classify targets and non-targets. The advantage of the logistic method is that it also quantifies a firm's takeover probability. The cut-off probability is used to classify targets and non-targets, where firms classified as targets have higher takeover probability than the cut-off probability and the opposite for non-targets. Palepu (1986) suggests finding the optimal cut-off probability as the intersection between the probability density functions of takeover probability of targets and non-targets over the estimation sample. He argues that this will theoretically minimize the number of misclassifications and in return generate a higher portfolio return. We present this method more detailed in Section 5.3, as we use it to derive one of our investment strategies.

The third and final section of Palepu (1986) that we find relevant for our thesis covers the takeover prediction models' ability to form the basis for successful investment strategies. Palepu (1986) is one of the first studies to examine whether the takeover prediction model is able to form the basis for investment strategies that generate market-adjusted excess returns. He divides his data in two samples, where the estimation sample is used to develop the takeover prediction model, while the holdout sample is the observations applied to test the models' ability to predict future takeover targets.

Palepu's (1986) investment strategy is to define a cut-off probability and invest in all companies with higher takeover probability than the cut-off probability. Palepu (1986) apply a cut-off probability of 11.2%, which results in 625 predicted targets and 492 predicted non-targets in the holdout sample. The actual targets and non-targets in the sample was 30 and 1,087, respectively. Thus, in the holdout sample test, 80% of the targets are successfully predicted, but this includes a large type II error (non-target incorrectly classified as target) of 55.3%, meaning that only 24 of the 625 predicted targets become actual targets. Over a period of 250 trading days, Palepu (1986) uses an equally weighted portfolio of the 625 predicted targets to test the model's ability to generate abnormal returns. The reported CAR for the portfolio is -1.6%, which is smaller than the CAR of non-targets at -1.5%. However, the actual 24 targets generate a CAR of 21.0%, while the six targets included in the non-target group generate a CAR of 36.2%. This indicate that unexpected targets or lower takeover probability results in higher CAR. Palepu's (1986) findings indicate that it is difficult to generate positive CAR based on prediction of the takeover likelihood model. Thus, the challenge is to construct a portfolio that contains a higher fraction of actual targets.

2.2.2 Related Empirical Evidence

In the following section, we examine related empirical studies for our paper. We review literature that uses Palepu (1986) as the basis for their empirical studies. These studies propose additional characteristics of takeover targets, which we will control for in our takeover prediction model for the Norwegian market. Moreover, the related empirical literature also discusses other investment strategies than the one Palepu's (1986) study applies. We find it appropriate to divide this section in a similar way as the latter. Hence, we first review characteristics of takeover targets other than those proposed by Palepu (1986). This is followed by an overview of the methodology. Third and finally, we examine empirical results from studies that test their takeover prediction models' ability to form the basis for successful investment strategies.

Table 2 summarizes the hypotheses and characteristics of takeover targets suggested by related empirical studies, including Palepu (1986). The table shows the independent variables, their expected sign and statistical significance.

Table 2 – Overview of previously proposed hypotheses and variables
This table summarizes the firm-specific hypotheses and statistical significance of the variables suggested in previous takeover prediction studies.

Hypotheses	Variables	Expected sign	Empirical study
Inefficient management	– Return on equity	-	Palepu (1986); Brar, Giamouridis & Liodakis (2009)
	– Abnormal return[4]	-	Palepu (1986); Ambrose & Megginson (1992)
	– Operating profit / capital employed	-	Powell (2001)
	– Tobin's Q	-	Cremers, Nair & John (2009); Brar, Giamouridis & Liodakis (2009)
	– Profit margin (& growth)** – Profits / capital – Asset turnover (& growth) – Market share – Return on sales – Return on capital – Sales growth*	-	Brar, Giamouridis & Liodakis (2009)

[4] Average excess stock return calculated with the market model and daily stock return data.

Firm size	– Net book assets	-	Palepu (1986); Ambrose & Megginson (1992); Powell (2001)
	– Market capitalization**	-	Barnes (1999); Cremers, Nair & John (2009); Brar, Giamouridis & Liodakis (2009)
	– Sales*** – Number of employees	-	Brar, Giamouridis & Liodakis (2009)
Growth-resource mismatch	– Growth-resource dummy (based on sales growth, liquidity and leverage)	+	Palepu (1986); Ambrose & Megginson (1992); Powell (2001)
MTB/ Undervaluation	– Price / earnings***	-	Palepu (1986); Ambrose & Megginson (1992); Brar, Giamouridis & Liodakis (2009)
	– Market / book	-	Palepu (1986); Ambrose & Megginson (1992); Powell (2001)
	– Dividend yield*** – Price / book		Brar, Giamouridis & Liodakis (2009)
P/E	– Price / earnings	-	Palepu (1986); Ambrose & Megginson (1992); Brar, Giamouridis & Liodakis (2009)
Leverage	– Long-term debt to assets		Brar, Giamouridis & Liodakis (2009)
	– Total debt to assets		Cremers, Nair & John (2009); Brar, Giamouridis & Liodakis (2009)
	– Short term debt to assets – Total debt to equity	+	Brar, Giamouridis & Liodakis (2009)
Liquidity	– Cash to capital***	-	Brar, Giamouridis & Liodakis (2009)
Ownership structure	– Number of institutional managers following firms – Percent of institutional shareholding – Change in institutional shareholding* – Percent of officer and director shareholding		Ambrose & Megginson (1992)
	– Dummy if institutional stockholder exists		Cremers, Nair & John (2009)

** and *** shows statistical significance at the 5% and 1% significance level, respectively

In addition to the six hypotheses proposed by Palepu (1986), related studies suggest testing for leverage, liquidity and ownership structure to differentiate targets from non-targets. Brar, Giamouridis and Liodakis (2009) argue that financially distressed companies are more likely to be targets. However, they do not find support for this hypothesis, as the variables are not statistically significant. Brar, Giamouridis and Liodakis (2009) also suggest the liquidity hypothesis, which proposes that firms with low liquidity are more likely to be takeover targets.

They find empirical support for this notion as cash-to-total assets is lower for targets than non-targets in their study. We find both of these hypotheses interesting for the Norwegian market, as asset-heavy firms dominate Oslo Stock Exchange (OSE). Thus, firms listed at OSE have both high debt levels and subsequently liquidity problems in poor market conditions.

The final firm specific variable we review is ownership structure. Holderness and Sheehan (1988) show that firms with an individual majority shareholder are less likely to partake in control transfers than companies with diffuse ownership. This can partially be explained by Thomsen and Pedersen (2000), who find that ownership concentration has a positive, but nonlinear relationship with economic performance. A strong owner enhances economic performance until the concentration reaches a certain point, leading to entrenchment and declining profitability. This implies that strong owners are equipped to discipline the management in the case of underperformance. Hence, takeovers as a disciplinary mechanism will not be necessary. Ambrose and Megginson (1992) test for the ownership structure hypothesis, in form of institutional and insider shareholders. They find that the percentage change in institutional shareholders has a statistically significant effect on the takeover likelihood.

In addition to the hypotheses and independent variables reviewed above, we find it interesting to present empirical evidence on how macroeconomic conditions affect takeovers. The aim is to broaden our view on which metrics that affect takeover likelihood to enrich our analysis of the Norwegian market. Becketti (1996) find that over one third of the variation in M&A activity in the US in the period 1960 to 1980 can be explained by macroeconomic factors. Bruner (2004) argues that macroeconomic factors, such as GDP, interest rates and fiscal policy, equity and debt capital market conditions, like risk premiums, credit ratings and betas, and customer behavior, like price elasticity of supply and demand, affect the takeover likelihood.

Steiner (1975) and Chung and Weston (1982) report that gross national product (GNP) and takeover activity is positively correlated in the US. Moreover, Golbe and White (1988) examine the GDP and find a positive correlation indicating higher takeover likelihood in an expanding economy. Shiller (1988) suggests that mass behavior in the financial markets affect the takeover likelihood, as high aggregated deal activity trigger takeovers due to firms taking advantage of being over- or undervalued. Rhodes-Kropf and Viswanathan (2004) and Rhodes-

Kropf, Robinson and Viswanathan (2005) find that high MTB ratios aligns with merger waves. They argue that MTB ratio is a proxy for market overvaluation and that investor's valuation error motivates merger activity.

Another macroeconomic factor that is widely studied is interest rates. As deal financing becomes cheaper with lower interest rates, many studies examine whether interest rates affect the takeover likelihood. Becketti (1986), Ploncheck and Sushka (1987), Yagli (1996) and Globe and White (1998) find that interest rates are negatively correlated with takeover activity. Thus, lower interest rates are often related to higher takeover likelihood. Ploncheck and Sushka (1987) also study the impact of unemployment on takeover activity. They find a negative relation between these two factors, implying that low unemployment increases the takeover likelihood. This is in line with the empirical result for GNP and GDP, discussed above.

Finally, oil prices influence takeover activity, especially at the OSE. EY (2017) argue that lower oil prices leading to lower valuations and higher debt-ratios encourage M&A activity. They argue that the deal level increases due to restructuring and bankruptcy. However, they also emphasize that appreciating oil prices positively affect takeover activity, as firms desire to expand and grow their businesses in such periods. Thus, both rising and falling oil prices encourage takeovers, but with different rationales. Indeed, falling oil prices drive deal activity first when the market believes the price has hit a bottom.

We now review the methodology applied in the empirical literature on takeover prediction models. Table 3 summarizes empirical studies and their choice of methodology.

Table 3 – Methodology in takeover prediction studies
This table gives an overview of methodological development in empirical studies on takeover prediction models over time.

Study	Methodology	Geographic region	Sample Period	Data
Palepu (1986)	Logistic regression	USA	1971-1979	163 targets and 256 non-targets
Ambrose & Megginson (1992)	Logistic regression	USA	1979-1986	169 targets and 267 non-targets

Powell (1997)	Logistic regression	UK	1984-1991	411 targets and 532 non-targets
Barnes (1999)	Logistic regression	UK	1991-1993	82 targets and 82 non-targets
Tsagkanos, Georgopoulus & Siripoulos (2006)	Conditional logistic regression	Greece	1995-2001	56 targets and 305 non-targets
Cremers, Nair & John (2009)	Logistic regression	USA	1981-2004	5,457 targets and 78,295 non-targets
Brar, Giamouridis & Liodakis (2009)	Logistic regression	Europe	1992-2003	262 targets and 722 non-targets

As shown in Table 3, all studies following Palepu (1986) use logistic regression to differentiate targets from non-targets based on publicly available information. The advantage of the logistic method is that it classifies targets and non-targets, as well as the probability of a firm being a takeover target. Barnes (1999) suggests a methodological improvement to Palepu's model by including an error minimization criterion through the profit-maximization criterion due to the goal to earn significant positive abnormal returns. However, few studies have adopted his suggestion. We share the view of Palepu and use a logistic regression to develop a takeover prediction model for the Norwegian market.

Finally, we review empirical evidence on whether takeover prediction models are able to form the basis for successful investment strategies. Miller and Modigliani (1961) propose that in efficient capital markets the share price reflects all information, including the market's assessment of a firm's takeover likelihood. That means a takeover prediction model would need to have a better predictive power than the market's assessment of the firm's takeover likelihood at the time of the prediction to generate an abnormal return. Table 4 reports CARs obtained in empirical studies, including Palepu (1986), by using the takeover prediction model as a basis for the investment strategy.

Table 4 – Obtained CAR in previous takeover prediction studies
This table gives an overview of the cumulative abnormal return over different investment periods based on the takeover prediction models in previous empirical studies.

Study	Cumulative Abnormal Return on Portfolio	Investment Period	Additional Information
Palepu (1986)	-1.6%	250 days	Investment portfolio consisting of all 625 predicted targets from the holdout sample of 1117 firms in 1980.
Powell (2001)	-11%***	1 year	Investment portfolio consisting of 216 predicted targets from the holdout sample of 1000 firms in 1996.
Brar, Giamouridis & Liodakis (2009)	+8.5%**	1 month	Investment portfolio consisting of upper 10% takeover likelihood firms with monthly rebalancing.
Cremers, Nair & John (2009)	11.8%***	1 year	Takeover-spread portfolio by buying the quintile of targets with highest takeover likelihood and shorting the quintile with lowest from 1981-2004.
	21.7%***	1 year	Same portfolio strategy, but in decile.

** and *** shows statistical significance at the 5% and 1% significance level, respectively

Powell (2001) argues that the high number of non-targets in the target portfolio dilutes the actual targets´ positive CAR. Moreover, Powell (2001) disagrees with Palepu's (1986) assumption that the cost of type I (target incorrectly classified as non-target) and type II errors (non-target incorrectly classified as target) are equal and constant. Powell (2001) argues that this is unrealistic as gains to target firms prior to a takeover exceed those to firms not taken over. Thus, he suggests a portfolio that focuses on maximizing the share of actual targets instead of Palepu's (1986) approach to minimize the number of misclassifications. Powell (2001) suggests determining the cut-off probability by organizing the observations in ten deciles that are analyzed for their concentration of actual targets and non-targets. The decile with the highest ratio of targets sets the cut-off probability as the lowest takeover probability in that portfolio. Despite these adjustments, Powell's (2001) portfolio gains a market-adjusted return of a significant -11%, which is worse than Palepu's (1986) results.

Brar, Giomouridis and Liodakis (2009) applies Powell's (2001) method and find the optimal cut-off probability to be 0.41. Based on an investment period of one year with monthly rebalancing, their investment strategy to acquire stocks in the top 10% takeover likelihood firms results in a significant CAR of 8.5% in an out of sample test. Moreover, Cremers, Nair and John (2009) constructs a long-short portfolio, which invests in companies with the highest takeover likelihood and shorts companies with the lowest takeover likelihood. Their portfolio generates a significant annualized abnormal return of 11.8% in the period 1981-2004. The same takeover portfolio with use of deciles generates an even higher return of 21.7%. However, as they do not test the model out of sample, the results can possibly be a result of "look-ahead bias" (see, e.g. Butler, Grullon and Weston, 2005). Their study points out that returns for firms with higher takeover exposure are higher and show that the constructed takeover factors add additional explanatory power to the four-factor Fama-French model (1992). Thus, the returns for companies with high takeover probability are generated due to both takeover bids and their higher exposure to takeovers.

3 Hypothesis Development

As mentioned, our paper aims to develop a takeover prediction model for the Norwegian market and test the model's ability to form the basis for successful investment strategies. In other words, we want to test whether it is possible to generate abnormal returns by investing in target firms predicted by our model. However, an underlying assumption for these objectives is that target shareholders in the Norwegian market experience positive CARs in takeovers. Thus, we first investigate empirically whether there are abnormal returns in Norwegian takeovers. Then, we develop a takeover prediction model and investigate its predictive power by selecting stocks based on its predictions. The literature review in Section 2 provides the background for developing the hypotheses on takeover announcement returns in Section 3.1 and takeover prediction in Section 3.2.

3.1 Hypothesis Related to Takeover Announcement Returns

The price impact of takeovers for target shareholders is widely researched across countries. Table 1 shows evidence of significant abnormal returns for target shareholders in takeovers over different event windows and geographical areas. In accordance with previous studies, we examine the following hypothesis:

H0. *There is no positive price impact of takeovers for target shareholders from t days prior to t days after the deal announcement.*

As the choice of event window affects target shareholders' abnormal returns, we test the hypothesis over several event windows. First, from 50 days prior to 50 days after the deal announcement. Second, from 20 days prior to 20 days after the deal announcement, and third, from 10 days prior to 10 days after the deal announcement. Additionally, event windows [-1,1], [-5,5], [-100,50] and [-250,50] are examined for the same hypothesis. Schwert (1996) and Eckbo (2009) argue that there is no significant run-up prior to two months before the deal announcement. Thus, we test over both long and short event windows. By using a long window, we capture both leaks in the pre-window and the outcome in the post-window. As our data includes only successful transactions, the post-window allows us to capture more of the total gain to target shareholders at OSE. However, as a longer window increases the risk of including noise, we also use short windows such as [-1,1] and [-5,5].

Moreover, following Eckbo and Solibakke (1991), the statistical significance of the run-up part of the CARs are tested. As run-up returns reflect the probability of a takeover before the deal announcement, it is interesting to examine both the magnitude of the price movement and the market's ability to predict takeovers. Thus, the outlined hypothesis is also tested over the event windows [-50,-1], [-20,-1] and [-10,-1]. The motivation behind testing these hypotheses is to confirm that target shareholders at OSE experience positive and significant CARs in takeovers. As this is the basis for developing a takeover prediction model and an underlying assumption to generate abnormal returns by investing in target firms, we find the result of this hypothesis interesting for our paper.

3.2 Hypothesis Related to Prediction of Takeover Targets

Based on related literature discussed in Section 2.2, we formulate ten hypotheses to differentiate target firms from non-target firms in the Norwegian market. These ten hypotheses form the basis for the independent variables included in our takeover prediction model. As discussed in Section 2.2, these hypotheses are frequently used to develop takeover prediction models and recognize takeover targets. The hypotheses and implied variables for firm-specific, industry-specific and macroeconomic factors are discussed below.

[1] *Inefficient management hypothesis: Underperforming firms are likely to be acquired.*

As discussed in Section 2.1, the inefficient management hypothesis is based on Manne (1965) and Jensen and Ruback (1983), who argue that takeovers are disciplinary acts that replace underperforming management of firms. They suggest that as managers compete for rights to control corporate assets, the superior, value-adding managers will eventually replace inefficient managers. We test for this hypothesis using the two independent variables in accordance with Palepu (1986) and Brar, Giamouridis and Liodakis (2009): 2-year sales growth and return on equity.

[2] *Firm size hypothesis: Smaller firms are more likely to be acquired.*

Second, we test whether takeover likelihood decreases with the size of the firm. A negative correlation between firm size and takeover probability has been proposed in several studies (see, e.g. Palepu, 1986; Ambrose & Megginson 1992; Brar, Giamouridis & Liodakis, 2009). To test for the firm size hypothesis, we include the logarithm of the annual sales in our takeover prediction model.

[3] *Growth-Resource mismatch hypothesis: An unbalance between a firm's financial resources and growth opportunities increases the likelihood of a takeover.*

As outlined in Section 2.2, we include the growth-resource mismatch hypothesis in the model. The underlying assumption is that firms with high growth opportunities, but scarce financial resources to exploit these, and vice versa, are likely to be acquired. To test for this hypothesis, we include a dummy variable in our model. To construct the dummy variable, we use two-year historical sales growth as a proxy for future growth opportunities, while financial resources are considered through liquidity and leverage. We measure liquidity as cash and equivalents to total capital, and leverage as debt-to-book value of equity. To distinguish between low and high values, we apply the median value within the industry for the specific year. Thus, the dummy variable equals to one for the combinations low growth - low leverage - high liquidity or high growth - high leverage - low liquidity.

[4] *Asset Undervaluation hypothesis: Firms with low market value relative to book value are likely targets.*

We develop the asset undervaluation hypothesis in the same manner as Palepu (1986). We investigate whether undervalued Norwegian firms are more likely to be takeover targets. The MTB ratio, defined as the market value of the firm's equity divided by its book value, is included in our model as a proxy for undervaluation. Hence, we test if low MTB firms tend to have a higher takeover likelihood. However, the difference in MTB ratios between firms could also be due to different expected growth rates and not necessarily misvaluation. As Palepu (1986) also mentions, the economic validity of MTB as a proxy for asset undervaluation is scarce.

[5] *Price-Earnings hypothesis: Firms with low P/E multiples are more likely targets.*

This hypothesis controls for mergers motivated by multiple arbitrage and is the last firm-specific variable Palepu (1986) applies in his takeover prediction model. Although he does not find the P/E variable statistically significant, it is used in several related studies (see, e.g. Ambrose & Megginson, 1992; Brar, Giamouridis & Liodakis, 2009). Thus, we include P/E, defined as market capitalization divided by earnings, in our takeover prediction model.

[6] *Leverage hypothesis: Firms with high leverage are more likely to be acquired.*

As discussed in Section 2.2, Brar, Giamouridis and Liodakis (2009) suggest that higher leverage increases the acquisition likelihood. Due to the cyclical nature of the main industries at OSE, we find it relevant to control for leverage. We use debt-to-book value of equity to capture the effect of leverage in our model.

[7] *Liquidity hypothesis: Lower liquidity increases the takeover probability.*

Related to the previous hypothesis, that likely targets have a weaker financial position, the liquidity hypothesis controls for financial capabilities in the short term. This hypothesis suggests that firms with low liquidity may be in financial distress or not be able to capitalize on profitable investment opportunities and thus not maximize shareholder value (Petersen, et al., 2017). This eventually attracts acquirers with financial power to realize these investments opportunities. Thus, firms with low liquidity are more likely to be takeover targets. Brar, Giamouridis and Liodakis (2009) find empirical evidence for this notion as cash-to-total assets is lower for targets than non-targets in their study. To test for this hypothesis, we incorporate cash-to-capital as a proxy for the company's ability to undertake profitable investment opportunities, and current ratio, defined as current assets divided by current liabilities, as a proxy for the short-term robustness of the firm in our model.

[8] *Ownership structure hypothesis: Firms with consolidated ownership are less likely to be acquired.*

As highlighted in Section 2.2, M&A as a disciplinary action against an underperforming management will be less likely in situations where a centralized ownership structure allows for better corporate governance. La Porta et al. (1999) and Faccio and Lang (2002) show that in most countries, except the Anglo-Saxon countries, large shareholders are common among listed companies. As mentioned, Døskeland and Mjøs (2008) document this for the Norwegian market. Thus, we believe that ownership structure is especially important to control for in the

Norwegian market. We include a Herfindahl index of ownership consolidation in our model to control for the hypothesis.

[9] *Industry disturbance hypothesis: Firms within industries subject to economics shocks are likely takeover targets.*

The industry disturbance hypothesis is based on the "economic disturbance theory" by Gort (1969). He argues that economic shocks trigger takeovers within an industry. Following Palepu (1986), we apply a dummy variable in our model to control for industry disturbance. This dummy equals one if there was at least one acquisition within the same SIC code in the previous year.

[10] *Macroeconomic factors hypothesis: Takeovers are more common when the economic environment supports merger activity.*

This hypothesis suggests that macroeconomic factors drive takeover activity, and in years with a deal friendly macroeconomic environment, firms are more likely to be takeover targets. We control for three macroeconomic factors as follows: First, as discussed in Section 2.2, multiple studies find a negative correlation between interest rates and takeover activity. Thus, our hypothesis is that lower interest rates increase the takeover likelihood. We include the Norwegian 10-year Government Bond in our model to control for this hypothesis. Second, EY (2017) states that both lower and higher oil prices can affect the takeover likelihood. Indeed, as OSE is an oil-heavy market, we find it relevant to control for oil prices. Our hypothesis is that there is a positive correlation between oil price and acquisition activity. To incorporate this in our model, we include the Brent Oil price. Third, it is often expected that the Norwegian Conservative Party facilitates stronger corporate position and optimism about the future among corporate managers. Hence, our hypothesis is that the Norwegian Conservative Party as the governing party is associated with more takeovers. We control for this through a dummy variable that equals one if the Conservative Party is governing in a specific year.

4 Data

We present the data used to assess the takeover announcement returns at the OSE in Section 4.1, the observations that are used to develop the prediction model in Section 4.2, and the holdout sample used to test the model's ability to generate an abnormal return in Section 4.3.

4.1 Data Related to Takeover Annoucement Returns

The data includes Norwegian publicly traded firms, excluding financial services that were acquired in the period 1995 to 2012. We made the choice to exclude financial services to ensure that the different interpretation of financial ratios of banks will not bias the results of our takeover prediction analysis. An additional requirement is that the bidder acquired more than 5% of outstanding target shares, which is the limit of shareholdings reporting in Norway (Finanstilsynet, 2015). Furthermore, to be included, the takeover needs to end with a post-transaction ownership of more than 33.4% of the company, which constitutes the limit for a mandatory bid for all outstanding shares in Norway (Finanstilsynet, 2015). We use these requirements to eliminate transactions that do not represent a change of control. Additionally, we collect stock prices from 250 trading days prior to 50 days after deal announcement for all target companies from the Bloomberg Terminal. From 1995-2012, there were 136 completed transactions at OSE registered in the SDC Platinum database that satisfied the deal-specific and information constraints. This lays the foundation for an event study and determining the CAR for each target. We use the MSCI World Index as a proxy for the market return to assess the abnormal return of the takeover targets.

4.2 Data Related to Prediction of Takeover Targets

A pooled sample of both targets and non-targets constitutes the estimation sample. We retrieve financial data from Amadeus 2.0 (the client for NHH Børsprosjektet), SDC Platinum, Bloomberg and SNF for the preceding year of all listed firms at OSE in the period 1995-2012. This result in a total of 153 transactions and 2,087 observations of non-targets that satisfy the information constraints from the ten hypotheses outlined in Section 3.2.[5] The macroeconomic

[5] The total number of transactions are higher than in the data related to the takeover announcement returns as information on historical share prices often failed to satisfy the information constraints.

factors; Brent Oil price, the rate of the Norwegian 10-year Government Bond and the governing party, are retrieved from Bloomberg, the Norwegian Central Bank and the Norwegian Government, respectively. Based on the collected information, we obtain both a target sample and a non-target sample. Table A1 and A2 in Appendix A presents descriptive statistics for the independent variables in the target and non-target sample. We use this publicly available information to develop the takeover prediction model for OSE.

Table 5 gives further insight into the estimation sample and the distribution of observations across industries. As the table shows, the fraction of targets within service industry is higher than the fraction of non-targets in the same industry, resulting in a positive difference of 10%. For the transportation and manufacturing industry, this delta is almost equal to zero, indicating that these industries are equally represented in the target and non-target samples. At last, we find that natural resources and other industries are underrepresented in the target sample compared to the non-target sample.

Table 5 – Estimation sample composition

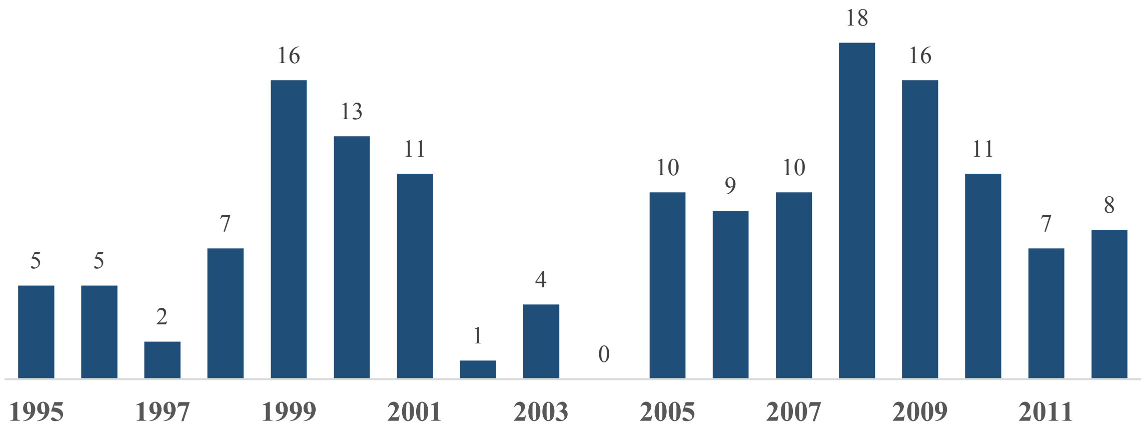
This table summarize the observations from the estimation sample. These observations are further separated between targets and non-targets, as well as how these are spread across different industries.

	Total		Target		Non-Target		Diff.
	No. of obs.	%	No. of obs.	%	No. of obs.	%	
Total	2 240	100.0 %	153	6,8 %	2 087	93,2 %	
Service	392	17,5 %	41	26,8 %	351	16,8 %	+10,0 %
Natural Resource	201	9,0 %	8	5,2 %	193	9,2 %	-4,0 %
Transportation	434	19,4 %	30	19,6 %	404	19,4 %	+0,2 %
Manufacturing	686	30,6 %	46	30,1 %	640	30,7 %	-0,6 %
Other	527	23,5 %	28	18,3 %	499	23,9 %	-5,6 %

4.2.1 Target Sample

Figure 1 displays the Norwegian deal activity over the estimation period (1995-2012), the overall trend was in line with the global merger waves in the period. The aggregate activity peaks in 1999-2000 and collapses with the dot-com bubble. Moreover, the sixth merger wave can also be witnessed in Norway before the financial crisis in 2007. In contrast to other markets, the deal activity continued to rise following the financial crisis in 2007. This can partially be explained by the high Brent Oil price volatility during that period, which made acquisitions of oil-related firms attractive at OSE. However, after 2009 the takeover activity in Norway also diminishes due to economic contraction.

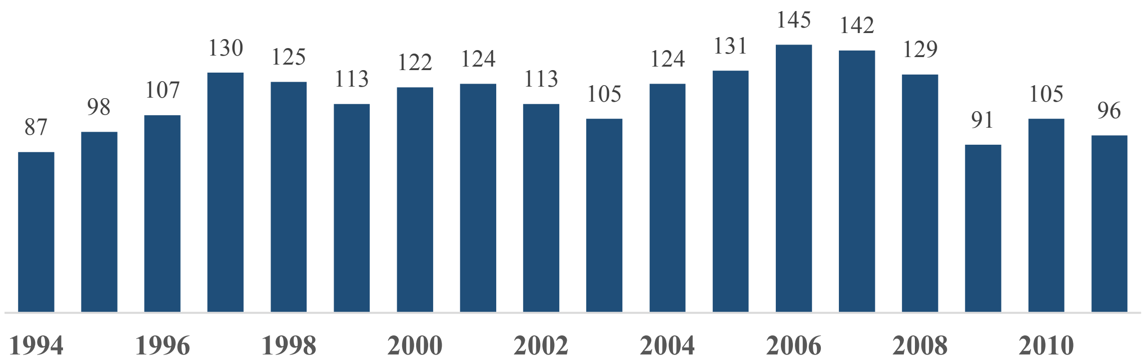
Figure 1 – Target sample over the estimation period
The data is based on the transactions recorded in SDC Platinum with sufficient information available.



4.2.2 Non-Target Sample

The non-target sample, or control group, comprises of 2,087 observations from 1994 to 2011. This sample has a more stable development over time than the target sample. One interesting observation is that the total number of publicly listed firms at OSE peaks one to two years before the peak of the fifth and sixth merger waves. This is consistent with the fact that in years with high takeover deal activity, the number of listed firms decreases due to delisting given relatively fewer initial public offerings.

Figure 2 – Non-target sample over the estimation period
The data is based on the publically traded firms recorded in Amadeus (NHH Børsprosjektet) with sufficient information available.



4.3 Data Related to Investment Strategies

The holdout sample contains Norwegian publicly listed companies from 2013 to 2016. The data collection is conducted in the same manner as for the two previous samples (see Table A4 and A5 in Appendix A for descriptive statistics). Firstly, the retrieval of financial data is done according to that in Section 4.2. We use this new sample to apply the prediction model and obtain an estimated takeover probability for each firm. Secondly, we collect historical stock prices to find the annual return of each firm in the holdout sample. This is utilized to test the successfulness of the model. Table 5 offers a decomposition of the sample, which includes 27 targets and 393 non-targets. We note that the distribution of targets is skewed towards the beginning of the period with two-thirds of the transactions occurring in the first two years. On an industry level, the transportation industry was most active in acquiring companies representing 29.6% of the total number of deals, while manufacturing was the second runner-up with 22.2% of the deals.

Table 6 – Holdout sample composition

This table summarize the observations from the holdout sample. These observations are further separated between targets and non-targets, as well as how these are spread across different industries and over the holdout sample period.

	Total		**Target**		**Non-Target**		**Diff.**
	No. of obs.	%	No. of obs.	%	No. of obs.	%	
Total	420	100.0 %	27	6.4 %	393	93.6 %	
Service	55	13.1 %	1	3.7 %	54	13.7 %	-10.0 %
Natural Resource	46	10.9 %	3	11.1 %	43	10.9 %	-0.2 %
Transportation	88	20.9 %	8	29.6 %	80	20.4 %	+9.2 %
Manufacturing	132	31.4 %	6	22.2 %	126	32.1 %	-9.9 %
Other	99	23.6 %	9	33.3 %	90	22.9 %	+10.4 %
2013	104	24.8 %	9	33.3 %	95	24.2 %	+9.1 %
2014	105	25.0 %	10	37.0 %	95	24.2 %	+12.8 %
2015	108	25.7 %	2	7.4 %	106	26.9 %	-19.5 %
2016	103	24.5 %	6	22.2 %	97	24.7 %	-2.5 %

By comparing industry distribution across the holdout sample and the estimation sample, we find that the fraction of targets within service industry is lower than the relative fraction of non-targets in the same industry, as the difference is negative 10% in the holdout sample. This distribution is contradictory to what we find for the service industry in the estimation sample, which indicates that actual targets in the holdout sample is underrepresented compared to the estimation sample. Moreover, we see that the difference is positive 9.2% for the transportation industry, indicating that service targets are overrepresented in the holdout sample, while they have almost equal relationship in the estimation sample. Finally, we also find a change in fraction of targets compared to non-targets in the manufacturing industry across the two samples, as the delta is -9.9% in the holdout sample, while it is -0.6% in the estimation sample. This means that takeovers within manufacturing are relatively underrepresented in the holdout sample compared to the estimation sample. Thus, there are some differences in the two samples. However, following Palepu's (1986) criticism of empirical studies prior to his, we correct for the methodological flaws by having an estimation and holdout sample that are random and non-equal-sized.

5 Methodology

In this section, we present the methodologies used to test the hypotheses from Section 3. This section consists of three stages. First, we describe the event study methodology for determining the takeover announcement return. Second, we present the logit regression approach and the functional relationship between the independent variables and the takeover likelihood. Finally, we examine the method for evaluating the predictive power of the takeover prediction model.

5.1 Methodology for Takeover Announcement Returns

To calculate the cumulative average abnormal return (CAAR) for target shareholders around deal announcement, we apply the standard event study methodology, as proposed by MacKinlay (1997). He proposes the market model as the foundation for calculating abnormal returns. The market model relates the return of a given security to the return of the market portfolio. Thus, the expected daily return is calculated as,

$$E(R_{i,t}) = \hat{\alpha}_i + \hat{\beta}_i R_{m,t} \tag{5.1}$$

where $R_{i,t}$ is the expected return of security i at day t, $R_{m,t}$ is the return of the market portfolio at day t, $\hat{\alpha}_i$ and $\hat{\beta}_i$ are the market-model parameters.

To estimate $\hat{\beta}_i$ for the various companies i, we use an estimation window that is unaffected by the takeover. As outlined in Section 2.1, Schwert (1996) and Eckbo (2009) argue that there is no significant run-up prior to two months before the deal announcement. Thus, to estimate the risk, we use an estimation period ending 50 days prior to announcement. This will exclude any run-up in the ordinary least square (OLS) model that determines expected return. MacKinlay (1997) argues that an estimation window should be minimum 120 trading days. Other researchers such as Brown and Warner (1985) and Goergen and Renneboog (2004) use 239 and 195 trading days, respectively. In this paper, we use an estimation period of 200 trading days.

Moreover, by applying the market model to measure the expected return, the abnormal return is calculated as the difference between the actual return and the expected return in the different event windows outlined in Section 4.1,

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) = R_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i R_{m,t}) \tag{5.2}$$

where $AR_{i,t}$ is the abnormal return of firm i at day t in the event period, $R_{i,t}$ is the actual return of firm i at day t in the event period. By summarizing the abnormal returns for each firm for the event window, the CAR for each firm is calculated as,

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} A\,R_{i,t} \tag{5.3}$$

where $CAR_i(t_1, t_2)$ is the cumulative abnormal return for firm i from the start of the event window, t_1, to the end of the event window, t_2. Finally, we find the CAAR by taking the average of the 153 target firms' CAR over the event window (MacKinlay, 1997). To examine whether CAAR is statistically significant, we test the null hypothesis that CAAR equals to zero in the event window. We apply the standard test statistics, as proposed by Brown and Warner (1985), to determine the statistical significance of the returns.

5.2 Methodology for Prediction of Takeover Targets

The aim of this study is to distinguish between targets and non-targets based on publicly available information. To test the hypotheses and the implied independent variables, we compare target firms to non-target firms in a specific year. In accordance with Palepu (1986) and other studies (see Table 3), we apply the logistic regression model, as there is a binary outcome where firms are either classified as targets or non-targets. Hence, we regress the independent variables on a target dummy to specify the functional relationship between firm-specific, industry-specific, macroeconomic factors and the acquisition likelihood.

The probability that the target dummy (Y) equals one is dependent on several explanatory variables (x). This conditional probability $\Pr\langle Y = 1 | X = x \rangle$ is rewritten as $p(x)$. The conceptual difference from linear function is that $p(x)$ must be between zero and one. To solve for this issue, Heldal (2006) use the logistic transformation, $log\frac{p}{1-p}$. This gives the logistic regression model,

$$logit\big(p(x)\big) = log\frac{p(x)}{1-p(x)} = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_k x_k \tag{5.4}$$

where log is the logarithm and x are the independent variables suggested by the ten hypotheses. By solving the previous equation for $p(x)$, the takeover probability can be stated in the form,

$$p(x) = \frac{e^{\alpha+\beta_1 x_1+\beta_2 x_2+\beta_3 x_3+\cdots+\beta_k x_k}}{1+e^{\alpha+\beta_1 x_1+\beta_2 x_2+\beta_3 x_3+\cdots+\beta_k x_k}} \tag{5.5}$$

To consider the period 1995-2012, as x are time-variant variables, and find the functional relationship between the independent variables and the takeover likelihood in a given period, we apply the equation below,

$$p(i,t) = \frac{1}{1+e^{-\beta x(i,t)}} \tag{5.6}$$

where $p(i,t)$ describes the probability that a firm i is taken over in period t, $x(i,t)$ represents a vector of the independent firm, industry and macroeconomic variables, and β represents a vector of parameters that has to be estimated.

5.3 Methodology for Investment Strategies

To assess the practical usefulness of the takeover prediction model, we will apply it in two different investment strategies. The strategies will each generate one equal-weight long-only portfolio at the first trading day in 2013. These portfolios will be annually rebalanced to reflect changes in takeover probabilities. In the case of any deal announcements, the stock will be held until the deal closes.

We will disregard any transaction costs as these are expected to be small given the annual rebalancing. The return from each strategy will be compared to the MSCI World Index to find the market adjusted return. As illiquid stocks are prevalent in the holdout sample, all stocks will be treated with the simplifying assumption of a beta equal to 1.[6]

The firms are classified as targets and non-targets by comparing the takeover probability estimated from the takeover prediction model to a predefined cut-off probability. If the estimated probability exceeds the cut-off probability, the firm is classified as a target. Our two investment strategies differ in how they calculate the cut-off probability and will be further described below.

Minimum Misclassifications

This approach is proposed by Palepu (1986). His study offers the objective of minimizing the number of misclassifications made by the model as this is hypothesized to result in a higher portfolio return. He assumes that it is equally costly to wrongly classify a target as non-target as it is to include an actual non-target in the investing portfolio. Based on Palepu (1986), we present the derivation of the minimal misclassification selection criterion below.

The market's assessment of the takeover probability is denoted as q. Further, we assume that it is common knowledge that the share price would be S_1 if the firm is acquired, and it is S_2 if it is not acquired. The current stock price, S, can therefore be explained by,

$$S = qS_1 + (1 - q)S_2 \tag{5.7}$$

Likewise, the payoff in each scenario can be denoted as $C_j(S_j - S)$. The relationship in eq. (5.7) ensures that, based on the probability q, the expected payoff is zero,

$$qC_1 + (1 - q)C_2 = 0 \tag{5.8}$$

However, with the takeover prediction model we obtain new private information that assesses the takeover probability for the firm to be k. Assuming that we agree with the market on the

[6] All illiquid stocks in the holdout sample are assumed to have a beta equal to 1. Thus, this assumption is only used in the investment strategies.

values of S_1 and S_2, we wish to exploit the new information we have obtained. Dependent on the relationship between q and k, the expected payoff changes (for us). The probability of a firm becoming a target given that we observe k from the model, can be described by applying the Bayes' formula,

$$P(target \mid k) = \frac{qP(k \mid target)}{qP(k \mid target) + (1-q)P(k \mid non - target)} \tag{5.9}$$

where $P(k|target)$ is the probability density of observing k conditional on the firm being a target and $P(k|non - target)$ is the same for non-targets. $P(k|target)$ is substituted into eq. 5.8, hence the firm is expected to have a positive payoff if,

$$P(target \mid k)C_1 + \big(1 - P(target \mid k)\big)C_2 \geq 0 \tag{5.10}$$

By substituting 5.9 into 5.10, the equation can be rewritten as,

$$\frac{P(k \mid target)}{P(k \mid non - target)} \geq \frac{-(1-q)C_2}{qC_1} \tag{5.11}$$

Thus, firms with a takeover probability k that satisfy eq. 5.11 have a positive payoff. Considering no budget constraints, investment returns are maximized if all firms that satisfy this condition are classified as targets and invested in. Firms that fail to satisfy the equation are classified as non-targets.

Given the relationship from eq. 5.8, the previous equation can be rewritten as,

$$\frac{P(k \mid target)}{P(k \mid non - target)} \geq 1 \tag{5.12}$$

Condition 5.12 indicates that the optimal selection criterion is to classify a firm as a target when the firm's marginal probability of observing k, given that the firm is a target, is higher than the corresponding marginal probability of observing k when the firm is a non-target. Thus, under the minimal misclassification strategy the cut-off probability is calculated as the intersection between the takeover likelihood distribution of actual targets and non-targets.

Maximum Targets

Powell (2001) argues that Palepu's (1986) assumption of the cost of Type I and Type II errors (loss of abnormal return) being equal and constant are unrealistic. He argues that the portfolio selection criterion should try to maximize the portion of targets in the portfolio rather than minimize misclassification as the objective is to generate an abnormal return. Thus, he proposes to divide the observations in the estimation sample into ten deciles based on their estimated takeover probability. Then, use the lowest takeover probability within the decile with the highest concentration of targets as the cut-off probability.

6 Empirical Results

In this section, we present the results of our analyses. In Section 6.1, we investigate the target announcement return of takeovers at the OSE in the period between 1995-2012. In Section 6.2, we develop the takeover prediction model and find the characteristics of takeovers at OSE. Finally, in Section 6.3, we test the model's ability to form the basis for successful investment strategies from 2013 to 2016.

6.1 Empirical results on Takeover Announcement Returns

Our results indicate that target shareholders at OSE experience positive and significant CAARs around announcement, which are in line with previous studies for other markets (see Table 4). The CAAR is 14.7%, 12.8% and 12.8% for the [-50,50], [-20,20] and [-10,10] event windows, respectively. As Table 7 shows, the majority of CAARs at different event windows are statistically significant at the 1% significance level. This leads us to reject the null hypothesis and conclude that target shareholders at OSE experience positive abnormal returns during takeovers. Moreover, run-up returns at OSE ranges between 0.8% and 2.8%, although not statistically significant. This correspond well to results from the Continental Europe, however much lower than those found in the UK and the US (Goergen & Renneborg, 2009; Schwert, 1996; Eckbo, 2009). This is likely due to the concentrated ownership structure at OSE, which results in less leakage due to fewer shareholders involved in the transactions (Døskeland & Mjøs, 2008). The results indicate that the market's expectation of a takeover at OSE is often equivalent to the rest of the Europe.

Table 7 – Cumulative average abnormal return over different event windows

This table contains CAAR for both announcement returns over various event windows and the run-up for Norwegian listed companies. For further insight, the sample is divided into natural resources and all other industries.

	Complete Sample		Other Industries		Natural Resources	
Event window	**CAAR (%)**	**t-value**	**CAAR (%)**	**t-value**	**CAAR (%)**	**t-value**
[-1,1]	+12.4%	6.20***	+12.8%	6.07***	+7.7%	+2.62
[-5,5]	+11.8%	4.79***	+13.2%	5.90***	-9.3%	-3.03
[-10,10]	+12.8%	4.64***	+15.6%	7.10***	-30.9%	-2.46
[-20,20]	+12.8%	4.14***	+15.8%	5.82***	-33.8%	-1.28
[-50,50]	+14.7%	3.78***	+18.7%	5.11***	-50.1%	-1.07**
[-100,50]	+13.9%	2.73***	+19.5%	4.10***	-76.5%	-0.42**
[-250,50]	+5.0%	0.81	+12.2%	2.21**	-109.8%	1.24**

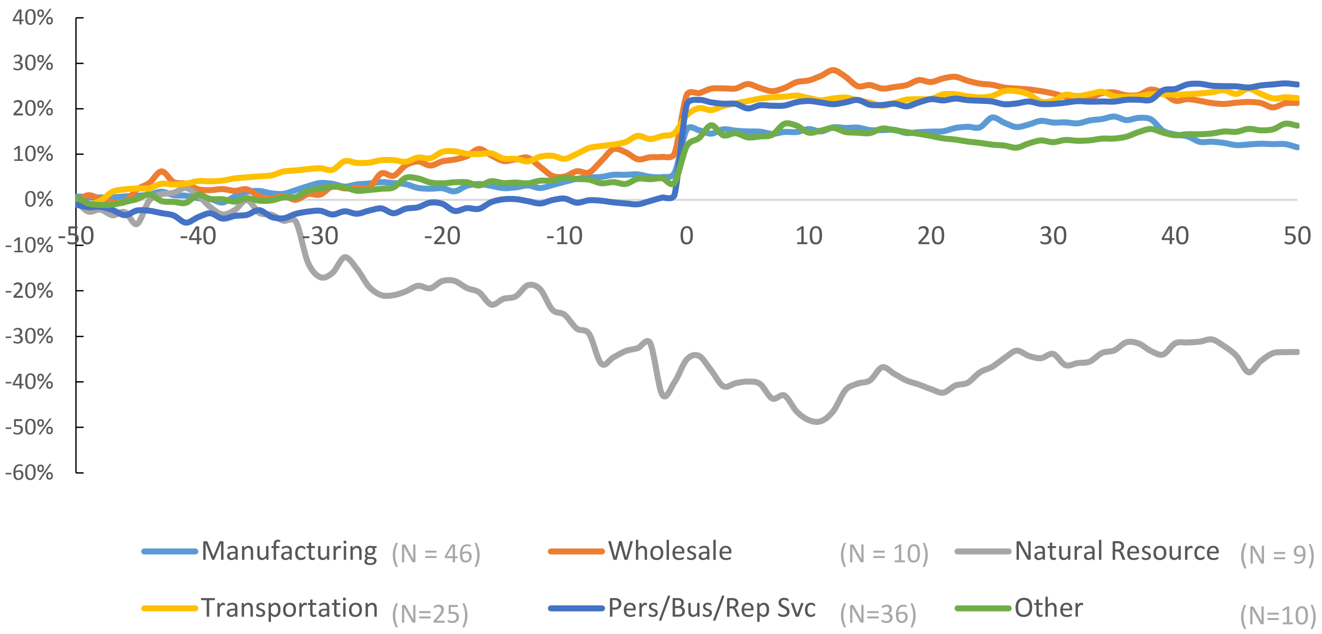
Run-up						
[-50, -1]	+2.8%	0.94	+6.0%	2.13**	-48.9%	-3.81***
[-20, -1]	+0.8%	0.40	+2.6%	1.56	-28.9%	-1.85
[-10, -1]	+1.1%	0.72	+2.4%	2.22**	-18.9%	-0.99
Observations	136		128		8	

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

Decomposition of CAAR at industry level gives further insight into the value creation of takeovers in the Norwegian market (see Figure 3). The clear outlier is the natural resources industry that experience negative CAAR in event windows longer than three days. However, only the natural resources' CAAR of -50.1%, -76.5% and -109.8% from [-50, 50], [-100,50] and [-250,10] trading days, respectively, are statistically significant. Takeovers within natural resources seems to offer a premium on the announcement day, but due to the ongoing target price depreciation prior to the deal announcement and a stable development afterwards, these takeovers do not offer value creation for target shareholders in the respective event windows. As the natural resources industry is cyclical, these results may be due to the mergers that occur as a consolidation of the industry in cyclical downturns (Gort, 1969).

On the other hand, overall CAAR and run-up, excluding natural resources, is significant 18.7% and 6.0% over event windows [-50,50] and [-50,-1], respectively. Moreover, the decomposition also shows that industries like services, wholesales and transportation on average experience higher CAAR than other industries. This can be related to the substantial synergies that takeovers in these industries offer (Porter, 1985). Compared to other industries, the run-up in wholesales and transportation starts earlier, which might be a result of these takeovers being easier to predict based on the strategic rationale of combining two firms. The implication of the analysis of CAAR across industries is that target firms within natural resources industry should be eliminated from the investment strategies, as these firms experience negative CAAR in takeovers.

Figure 3 – CAAR for event window [-50,50]
Cumulative average abnormal returns for the hold out sample in the period from 50 days prior to the announcement to 50 days after separated on the various industries.



In this section, we have established that target shareholders at OSE receive a substantial, statistically significant premium in takeovers. By excluding natural resources, the target shareholder CAAR of 18.7% from 50 days prior to 50 days after the deal announcement is line with Goergen and Renneboog's (2004) results for Continental Europe. Based on the analysis above, we find it interesting to develop two investment strategies in Section 6.3; one that includes targets from all industries, and another that excludes natural resources firms, but includes all other industries.

6.2 Development of the Takeover Prediction Model

Based on the ten hypothesis presented in Section 3.2, we develop four takeover prediction models. The first model includes the firm-specific hypothesis (inefficient management, growth-resource mismatch, firm size, MTB and P/E) suggested by Palepu (1986), as well as Gort's (1969) theory of industry disturbance. Thus, the first model effectively replicates the initial study performed by Palepu (1986) on the Norwegian market. The second model, in accordance with Brar, Giamouridis and Liodakis (2009), incorporates the hypothesis of liquidity, leverage and sales growth. The third model includes the macroeconomic variables and current ratio, while it excludes leverage as it is insignificant in the second model. The industry disturbance dummy is replaced with the actual number of transactions in an industry in the previous years. In addition, as suggested by Ambrose and Megginson (1992), ownership structure is incorporated by including the Herfindahl Index of ownership. The fourth model is adjusted to exclude variables that is less relevant for explaining takeovers in the Norwegian market. The table below shows our results.

Table 8 – Fixed effects logit regressions for takeover prediction

This table summarizes the results from four different regression models. Model 1 uses the firm specific variables proposed by Palepu (1986) and controls for industry disturbance. Model 2 includes additional firm specific variables such as growth, leverage and liquidity to recreate Palepu's final prediction model on the Norwegian market. Model 3 includes a wider set of variables to allow for adjustments based on ownership structure as well as specific factors for the Norwegian market. Model 4 reduces the number of variables to only include the 9 most influential factors.

	Estimates			
Variables (Expected Sign)	Model 1	Model 2	Model 3	Model 4
Growth (-)		-1.085***	-0.992**	-0.954**
		(-2.79)	(-2.37)	(-2.31)
Return on Equity (-)	-0.437**	-0.403*	-0.507**	-0.382
	(-1.97)	(-1.78)	(-2.08)	(-1.64)
ln[Sales] (-)	1.080***	1.415***	0.872***	0.901***
	(4.82)	(4.56)	(2.59)	(2.74)
Growth-Resource Mismatch (+)	-0.421*	-0.219	-0.0606	
	(-1.71)	(-0.86)	(-0.23)	
Price to Earnings (-)	0.00250	0.00254	0.00210	
	(1.27)	(1.29)	(1.01)	
Market to Book (-)	-0.126*	-0.116*	-0.0950	
	(-1.86)	(-1.76)	(-1.63)	
Leverage (+)		-0.0345		
		(-0.53)		
Cash to Total Capital (-)		-3.469**	-5.442***	-5.898***
		(-2.35)	(-3.18)	(-3.50)
Current Ratio (-)			0.106**	0.117**
			(2.13)	(2.35)
Ownership Concentration (-)			-1.319	-1.369*
			(-1.58)	(-1.65)
Industry Disturbance Dummy (+)	0.188	0.242		
	(0.65)	(0.82)		
Industry Disturbance (+)			0.217*	0.231**
			(1.90)	(2.06)
Brent Oil [USD] (+)			0.0184***	0.0188***

			(2.97)	(3.17)
10 Year Norwegian Bond (-)			-0.511***	-0.514***
			(-3.43)	(-3.52)
Governing Party (+)			-0.139	
			(-0.41)	
No. of observations	836	836	836	836
Likelihood ratio Chi^2	48.54	68.38	107.70	102.40
Probability > Chi^2	0.0000	0.0000	0.0000	0.0000
Pseudo R^2	0.1060	0.1494	0.2353	0.2237

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

As our results show, there are several variables that affect takeover likelihood of firms at OSE. In line with Manne (1965) and Jensen and Ruback (1983), we find some evidence for ROE across our takeover prediction models. The negative coefficient of ROE lends it's support to the hypothesis that underperforming management increases takeover likelihood for Norwegian publicly listed companies. This indicates that target firms tends to have lower ROE than non-target firms, but it is uncertain if this is due to underperforming management or industry characteristics. In Table B1 (see Appendix B), we perform the same analysis with industry-adjusted variables and find that industry-adjusted ROE is insignificant. Thus, the initial evidence on ROE could be a result of industry characteristics rather than underperforming management. On the other hand, we find significant evidence for the sales growth variable, which also represents the inefficient management hypothesis. This result indicates that low growth firms at OSE are more likely to become takeover targets.

Further, we find significant evidence for the firm size hypothesis. However, the sales variable has a positive sign, which is contradictory to the hypothesis and Brar, Giamouridis and Liodakis's (2009) empirical results, as it indicates that larger firms are more likely targets. We believe this might be related to the relative size of international competitors. Moreover, as the growth-resource dummy is only signifiant at the 10%-level and in the first model, we find marginally significant evidence for the growth-resource mismatch hypothesis. The dummy is negative and contrary to the expectation, which implies that companies with growth-resource mismatch have lower takeover probability. We also find marginal evidence for MTB ratio. Thus, in line with Rhodes-Kropf, Robinson and Viswanathan (2005), our results, to some degree, indicate that low MTB ratio firms are more likely acquisition targets in Norway.

Following Brar, Giamouridis and Liodakis (2009), we find significant evidence for the liquidity hypothesis across our takeover prediction models. The negative sign indicates that firms with low liquidity relative to total assets have higher takeover likelihood. We find this result interesting, as the Norwegian market is characterized by asset-heavy firms operating in cyclical industries. Our results confirm again that liquidity is essential for these firms to survive in economic downturns. The lack of liquidity to repay debt and interest can result in financial distress and higher interest from potential bidders seeking to take advantage of assets on discount. This eventually lead to higher takeover probability for firms with low liquidy relative to total assets.

We also find current ratio, Norwegian 10-year Government Bond and Brent Oil price significant at the 5%-level, while industry disturbance and ownership structure are marginally significant. However, the positive coefficient of current ratio is contradictory to the hypothesis. On the other hand, the signs of industry disturbance, ownership strucutre, Norwegian 10-year Goverment Bond and Brent Oil price support the hypotheses. As Gort (1969) suggests, the hypothesis that economic shocks within Norwegian industries trigger mergers and increase the takeover likelhood is to some degree confirmed. We also find marginal evidence for the proposition that concentrated ownership decrease takeover likelihood due to better corporate governance (Thomsen & Pedersen, 2000). In accordance with Becketti (1986) and other studies, we find support for the hypothesis that lower interest rates increase takeover likelihood for Norwegian firms. Finally, as EY (2017) proposes, relatively higher Brent Oil price also tends to increase acquisition probability at OSE.

As mentioned, the independent variables in these takeover prediction models are not adjusted for industry. Thus, we conduct the same procedure as above on industry-weighted variables. Appendix B present the results, and does not show many statistical significance variables. The only different between Table 8 and Appendix B is that the independent variables are adjusted by the median within a SIC in a specific year.

In the following section, we use the fourth model to test the ability to generate abnormal returns by investing in predicted targets. The fourth model includes the nine independent variables that have been the most influential in the three first models. This indicates that the hypotheses 1-2 and 7-10 from Section 3.2 are deemed most influential in determining targets at OSE and explain 22.4% of the acquisitions.

6.3 Prediction Tests

In this section, we will first discuss the predictive power of the model and then apply investment strategies to test the model's ability to generate abnormal returns. We use two different strategies that differ in their approach to determining the cut-off probability for classifying a firm as a target. Thereafter, we test the portfolios constructed by these two approaches using a holdout sample containing publicly traded companies at OSE from 2013 to 2016.

6.3.1 Predictive Power of the Model

Based on the fourth model developed in Table 8 (Section 6.2), we estimate the takeover probabilities for the 420 companies in the holdout sample. We observe that the targets in the sample receive an average estimated takeover probability of 36.6%. The same figure for non-targets is 27.6%. Hence, the model seems to detect some characteristics that characterize an attractive acquisition target. By using the takeover likelihood, we rank potential targets and non-targets and group them in deciles. This allows for a comparison of portfolio returns given the different estimated takeover probabilities, and thus an indication of the success of the prediction model. Table 9 provides the number and percentage of targets and non-targets in probability ranked deciles with the lowest probability in the 1th decile and the highest in the 10th. The distribution of targets seems to have a concentration towards the high-probability deciles. Indeed, the average target concentration among the top five deciles is 7.1%, which is higher than the overall sample at 6.4%. Furthermore, the 10th decile contains 16.7% targets, 2.6 times more targets than the overall sample. Thus, our results indicate some degree of predictive power of the model.

Table 9 – Prediction model accuracy

The distribution of targets and non-targets from the results of the prediction model. The table shows the fraction of targets and non-targets predicted by the model based on how likely they are to be targets. Decile 1 being the predicted least likely targets and decile 10 being the most likely targets.

Takeover Likelihood												
Decile (d)	1 (lowest)	2	3	4	5	6	7	8	9	10 (highest)	Total	Diff.
Actual targets	3 7.14 %	3 7.14 %	2 4.76 %	2 4.76 %	2 4.76 %	1 2.38 %	2 4.76 %	3 7.14 %	2 4.76 %	7 16.67 %	27 6.43 %	10-1.d 9.53%
Actual non-targets	39 92.86 %	39 92.86 %	40 95.24 %	40 95.24 %	40 95.24 %	41 97.62 %	40 95.24 %	39 92.86 %	40 95.24 %	35 83.33 %	393 93.57 %	10-1.d -9.53%
Total	42	42	42	42	42	42	42	42	42	42	420	

Table 10 illustrates the market adjusted annual returns generated from the 10 decile portfolios. The results are not consistent with the hypothesis of earning abnormal return by predicting takeover targets and might therefore indicate an insufficient prediction model or too short time period (only four years). We further examine the model's ability to earn significant and positive abnormal returns in the next section.

Table 10 – Portfolio return based on predicted probability
This table shows the investments returns from investing in the different deciles with annual rebalancing. Decile 1 is the 10% least likely targets for any given year.

		Market (MXWO) Adj. Annual Return				CAAR
Deciles		2013	2014	2015	2016	2013-16
1	Lowest	184.1 %	15.0 %	23.1 %	11.2 %	58.4 %
2		13.5 %	-0.1 %	-6.2 %	20.1 %	6.8 %
3		5.4 %	2.6 %	24.1 %	4.4 %	9.1 %
4		-9.4 %	0.5 %	-7.3 %	40.9 %	6.2 %
5		45.2 %	15.4 %	-4.5 %	1.1 %	14.3 %
6		-15.5 %	-6.6 %	7.3 %	16.0 %	0.3 %
7		5.8 %	-7.8 %	3.5 %	1.1 %	0.6 %
8		12.8 %	-5.3 %	-4.3 %	-1.4 %	0.5 %
9		-3.5 %	-23.2 %	23.6 %	13.3 %	2.5 %
10	Highest	5.2 %	-8.1 %	-15.9 %	3.1 %	-3.9 %
Diff decile 10 - 1		-178.9 %	-23.1 %	-39.0 %	-8.1 %	-62.3 %

6.3.2 Estimation of cut-off probabilities

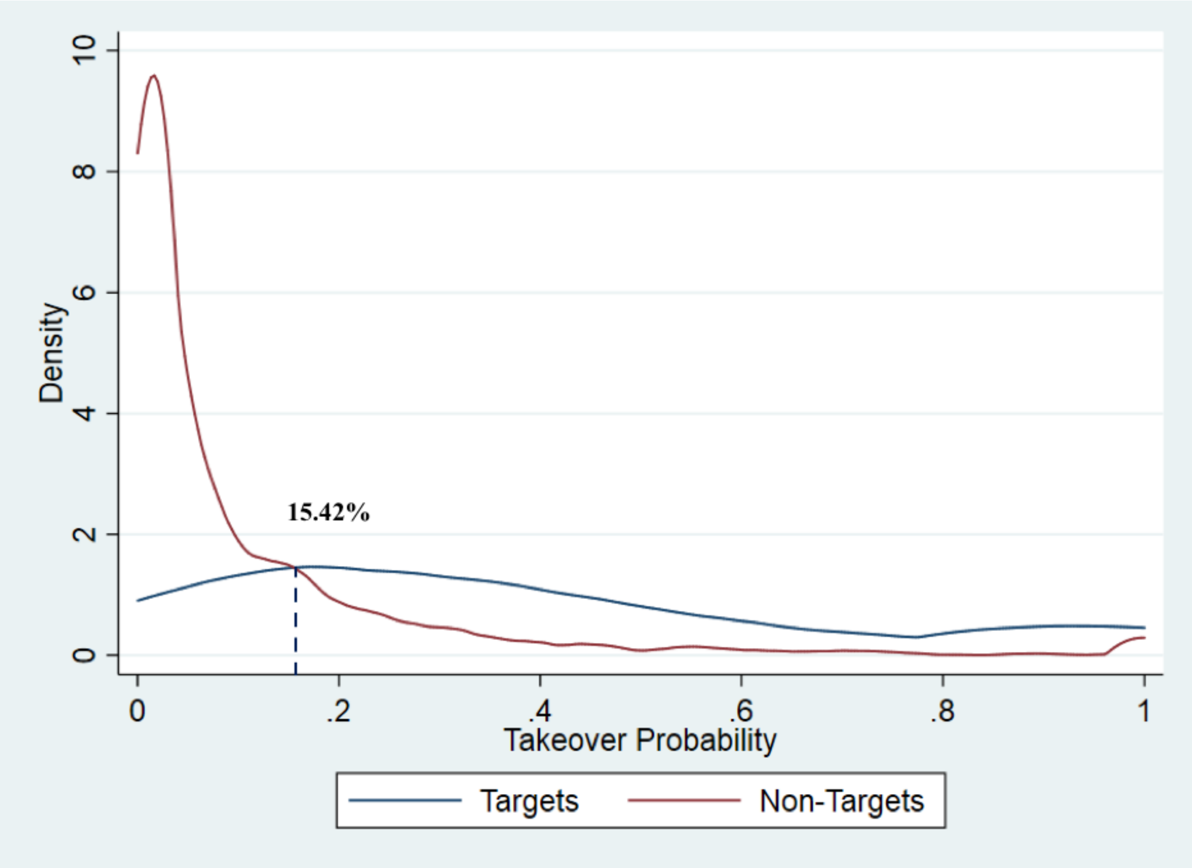
We use two different investment strategies to test the model from Section 6.2. The difference between these is their approach to separating targets from non-targets. All firms classified as targets will be included in the portfolio. We outline the way these two strategies estimate the cut-off probability below.

Minimal Misclassification cut-off probability

The first investment strategy is derived from the objective to minimize misclassifications when determining targets and non-targets. Palepu (1986) suggests this could be achieved by using the intersection of the probability distributions for targets and non-targets in the estimation sample as the cut-off probability. Figure 4 shows that there is clear difference in takeover probability for future targets compared to non-targets. The density of the target takeover probability crosses that of the non-targets at a 15.42% probability. This entails that firms with takeover probabilities higher than 15.42% in the holdout sample are classified as targets under the minimal misclassification approach.

Figure 4 – Probability density function

This figure shows the probability density function for both targets and non-targets in the estimation sample.



With the 15.42% cut-off probability as the basis, the model predicts a total of 297 targets in the period between 2013-2016. This is substantially higher than the 27 actual targets in the holdout sample. The excessive size of the portfolio will not only make it difficult to implement but will also have a dilutive effect on the actual targets contribution to the portfolio return. Indeed, with 19 of the 297 firms in the portfolio correctly classified as targets the target ratio is no better than the overall sample. The results show a type I error (where actual targets are misclassified as non-targets) of 8. Moreover, 115 non-targets being correctly classified indicates a type II error (where non-targets are misclassified as targets) of 278. These results are consistent with Palepu (1986), who also has a large type II error.

Table 11 – Portfolio composition using the minimal misclassification cut-off probability
The predicted targets each year constitutes the portfolio. The table shows the number of correctly predicted targets and how this compares to the actual number of targets. The same is done for non-targets.

	Targets			Type I error	Non-Targets			Type II error
Sample	Predicted	Correct	Actual		Predicted	Correct	Actual	
Entire	297	19	27	8	123	115	393	278
2013	82	9	9	0	22	22	95	73
2014	92	7	10	3	13	10	95	85
2015	76	2	2	0	32	32	106	74
2016	47	1	6	5	56	51	97	46

Maximum Target cut-off probability

We also use the alternative selection criterion for which companies to include in the investment portfolio, suggested by Powell (2001), that were discussed in Section 5.3. We look at the composition of firms in the deciles discussed in Section 6.3.1. With a concentration ratio (C-ratio) of 31.25% in the 10th decile, we find the corresponding cut-off probability of 33.65% from Table 12. The table also reports the characteristics of portfolios created from the cut-off probability from each decile. We see that the 10th decile portfolio also has the most correctly predicted targets overall.

Table 12 – Concentration ratios and sample discrimination
This table present the characteristics of the ten decile portfolios.

	Concentration Ratio (C-Ratios)					Discrimination within Sample					
Decile	No. of Firms	No. of Targets	Non-Targets	C-ratio	Cut-off	Targets	Non-Targets	Type I Error	Type II Error	Total Correct	Targets in Portfolio
Model 4											
1	224	5	219	2.23 %	0.00 %	153	0	0	2,087	16.61 %	6.83 %
2	224	1	223	0.45 %	0.19 %	148	219	5	1,868	16.38 %	7.34 %
3	224	5	219	2.23 %	0.48 %	147	442	6	1,645	26.29 %	8.20 %
4	224	3	221	1.34 %	1.18 %	142	661	11	1,426	35.85 %	9.06 %
5	224	3	221	1.34 %	2.43 %	139	882	14	1,205	45.58 %	10.34 %
6	224	5	219	2.23 %	4.12 %	136	1,103	17	984	55.31 %	12.14 %
7	224	13	211	5.80 %	6.77 %	131	1,322	22	765	64.87 %	14.62 %
8	224	15	209	6.70 %	11.66 %	118	1,533	35	554	73.71 %	17.56 %
9	224	33	191	14.73 %	18.54 %	103	1,742	50	345	82.37 %	22.99 %
10	**224**	**70**	**154**	**31.25 %**	**33.65 %**	**70**	**1,933**	**83**	**154**	**89.42 %**	**31.25 %**
Total	2,240	153	2,087								

Applying the 33.65% cut-off probability results in a much smaller and effortlessly implemented portfolio. The number of firms in the portfolio for each year ranges between 20 and 35. With 11 correctly predicted targets, or 10.00 % of the total portfolio, the model proves to have some predictive power. Moreover, this approach yields a significantly lower number of misclassifications with 16 type I errors and 99 type II errors. However, the strategy does not correctly predict any targets in the two final years.

Table 13 – Portfolio composition using the maximum targets cut-off probability
The predicted targets each year constitutes the portfolio. The table shows the number of correctly predicted targets and how this compares to the actual number of targets. The same is done for non-targets.

	Targets			Type I error	Non-Targets			Type II error
Sample	**Predicted**	**Correct**	**Actual**		**Predicted**	**Correct**	**Actual**	
Entire	110	11	27	16	310	294	393	99
2013	28	6	9	3	76	73	95	22
2014	35	5	10	5	70	65	95	30
2015	27	0	2	2	81	79	106	27
2016	20	0	6	6	83	77	97	20

6.3.3 Excess Returns from Investment Strategies

By investing in the two sets of portfolios generated in Section 6.3.2. on the first trading day of the year with annual portfolio rebalancing, we get the returns displayed in Table 14. The MSCI World Index appreciated 7.4% annually over the period. The annual return of the investment strategies where 9.2% and 8.3% for the minimal misclassification and maximum targets approach, respectively. Thus, contrary to the positive findings regarding the portfolio composition for the maximum target strategy, the return is lower than for the minimal misclassification approach. As the trading volume for some of the companies in the sample is low, the assumptions related to the *Capital Asset Pricing Model* do not hold and the calculation of abnormal return is based on an assumed beta of 1. Hence, the minimal misclassification strategy successfully outperforms the market with 1.8% per annum over the period. However, the market adjusted return is not significantly different from zero. The maximum target strategy also outperforms the market with an adjusted return of 0.9%, although not statistically significant.

Table 14 – Market adjusted return for the two investment strategies
This table compares the return generated from the takeover prediction model under the two investment strategies to the return of the MSCI World Index.

	MXWO	Minimum Misclassifications		Maximum Targets	
		Return	Market Adj.	Return	Market Adj.
2013	24.1 %	30.1 %	6.0 %	31.4 %	7.3 %
2014	2.9 %	-1.8 %	-4.4 %	-9.3 %	-12.2 %
2015	-2.7 %	-2.5 %	0.3 %	-2.4 %	0.4 %
2016	5.3 %	10.9 %	5.6 %	13.5 %	8.2 %
CAAR 13-16	7.4 %	9.2 %	1.8 %	8.3 %	0.9 %
(T-statistics)			(0.47)		(0.14)

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

A decomposition of the return generated over the whole holdout sample, shows that the non-targets have outperformed the actual targets. The companies that are not acquired during the holdout period generate an average market adjusted annual return of 10.3%, while the targets experienced a -3.3% market-adjusted return. We notice the same tendencies in the investment strategies as all positive contribution to the market-adjusted return derives from the non-targets included in the portfolios. As the type II errors drive the return generated from the takeover prediction portfolios, we question the effectiveness of the model. Even by refraining from investing in firms within the natural resources industry, which had negative CAAR, the results worsen (see Appendix C). The results indicate that the model does not perform better than the overall market at detecting takeover targets and capitalizing on their announcement returns. Our results are therefore consistent with those of Palepu (1986) and Powell (2001), and our takeover prediction model also does not reflect a viable investment strategy.

Table 15 – Market adjusted return decomposition
This table decompose the market adjusted annual return to separate the abnormal return contribution from targets and non-targets in the sample and in the proposed portfolios given by the two investment strategies.

	Sample			Minimum Misclassifications			Maximum Targets		
	Targets	Non-Targets	Total	Targets	Non-Targets	Portfolio	Targets	Non-Targets	Portfolio
2013	-4.4 %	27.9 %	25.4 %	-4.4 %	7.2 %	6.0 %	-1.6 %	9.8 %	7.3 %
2014	18.0 %	-3.9 %	-1.8 %	-0.8 %	-5.1 %	-4.7 %	-14.4 %	-11.9 %	-12.2 %
2015	-20.9 %	5.1 %	4.6 %	-20.9 %	0.8 %	0.3 %	0.0 %	0.4 %	0.4 %
2016	-5.7 %	12.2 %	11.2 %	-85.5 %	7.5 %	5.6 %	0.0 %	8.2 %	8.2 %
CAAR 13-16	-3.3 %	10.3 %	9.8 %	-27.9 %	2.6 %	1.8 %	-4.0 %	1.6 %	0.9 %

7 Conclusion and Possible Extension

The purpose of this thesis was to extend the existing takeover prediction literature by applying known takeover influence factors on the Norwegian market as well as include a set of variables relevant for the takeover activity in Norway. With a cumulative abnormal return for target shareholders of 14.7% over a [-50,50] window, or 18.7% over a [-50,50] window when natural resources firms are excluded, a successful prediction model should be able to deliver a return better than the overall market. However, by analyzing characteristics of all public takeovers at Oslo Stock Exchange in the period from 1995 to 2012, the approach was not able to predict takeover targets for an investment strategy that generated a market adjusted positive return for the four succeeding years.

We find evidence in line with previous research in that underperforming firms and companies with poor liquidity is more likely to become targets. On the other hand, we find marginal evidence for the hypothesis that companies with consolidated ownership are less likely to be subject to disciplinary action as the current owners are equipped to secure adequate corporate governance. On an industry-level, there is some evidence that takeovers within an industry cluster in specific consolidation periods. On the oil-heavy Oslo Stock Exchange, we expected this to occur more frequent than in better diversified markets. Especially within natural resources, takeovers follow large declines in share price. The aggregated level of M&A is subsequently correlated with the Brent Oil price and the access to cheap financing through low interest rates.

By controlling for these factors, the model was able to include 10% of actual targets in the portfolio under the maximum target investment strategy. This is better than the 6.4% fraction of targets in the complete holdout sample. However, the maximum target strategy generated an annual market adjusted return of 0.9% compared to 1.8% return of the minimal misclassification approach. This is surprising as the latter had the same fraction of targets as the complete holdout sample. However, the positive returns were not statistically significantly different from zero. Furthermore, much of the return was driven by type II errors. Hence, we conclude that an investment strategy based on this takeover prediction model in the Norwegian market is not a viable investment strategy.

If further research on drivers of M&A in the Norwegian market were able to improve the results from this thesis, the possible applications of the prediction model outside an investment strategy are numerous. Corporate advisers (investment bankers, lawyers and consultants) can benefit from a prediction model by streamlining the screening process and therefore be able to spend more time on due diligence of potential targets predicted by the model. By knowing which companies they are pitching potential targets to, they can further ease the process by pinpointing the exact industry SIC code they want to acquire from. Such a model might also benefit the players in the market for corporate control. Managers may wish to estimate the likelihood of their company being acquired, or even a methodological approach to finding potential takeover targets for themselves. The asymmetric information that the managers possess over the market should deem them better equipped to estimate a takeover likelihood, but a quantitative structuring of the procedure might give new insights into the process. Furthermore, investors and hedge funds maintaining their short positions can benefit from a quantitative approach to determine the likelihood that an acquisition could occur as this could offer huge losses.

Besides applications with a pure economic incentive, such a model could be of great relevance for regulators who try to protect minority interests. M&A is viewed as a disciplinary action, but to what extent it replaces poor corporate governance is something that would be interesting for further research. Thus, it would be relevant to analyze whether takeovers caused by ineffective management are more frequent in regions where poor regulations and a particularly scattered ownership structure make corporate governance more difficult. This could enrich regulator insight into how they should impose regulations to secure minority interests. However, due to limited data, we have not been able to incorporate these subjects, and they remain open for further research.

8 Appendix

A Descriptive statistics for the estimation and holdout sample

Inefficient management hypothesis

Sales growth:

Method: Sales growth calculated as Sales (t) / Sales (t-1)

Source: Data retrieved from NHH Børsdatabasen

Elimination: Observations with one year sales growth lower than -80% and higher than 4000% dropped. Observations with two year sales growth lower than -80% and higher than 5000% dropped.

EBITDA margin:

Method: EBITDA divided by sales

Source: Data retrieved from NHH Børsdatabasen

Elimination: Observations with EBITDA margin lower than -200% and higher than 200% dropped.

ROE:

Method: Net income divided by book value of equity.

Source: Data retrieved from NHH Børsdatabasen.

Elimination: Observations with ROE lower than -500% and higher than 1000% dropped.

Firm size hypothesis

Method: Sales, total assets and market capitalization used as proxy for firm size.

Source: Data retrieved from Bloomberg and NHH Børsdatabasen.

Elimination: Observations with market capitalization lower than 1000 dropped. Observations with sales lower than 500 dropped.

Growth-resource mismatch hypothesis

Method: Described in Section 3.2.

Source: Data retrieved from NHH Børsdatabasen.

Elimination: None.

Undervaluation hypothesis

Method: Market-to-book calculated as market capitalization divided by book value of equity.

Source: Data retrieved from Bloomberg and NHH Børsdatabasen.

Elimination: Observations with MTB lower than -10 and higher than 50 dropped.

Price-earnings hypothesis

Method: Price-to-earnings calculated as market capitalization divided by net income.

Source: Data retrieved from Bloomberg and NHH Børsdatabasen.

Elimination: Observations with PE lower than 200 and higher than 500 dropped.

Leverage hypothesis

Method: Debt-to-book value of equity calculated as interest-bearing debt divided by book value of equity and debt-to-market capitalization calculated as interest-bearing debt divided by market capitalization.

Source: Data retrieved from Bloomberg and NHH Børsdatabasen.

Elimination: Observations with missing values for debt-to-BVE dropped.

Liquidity hypothesis

Method: Cash-to-capital calculated as cash flow from operations divided by capital expenditure, and current ratio, defined as current assets divided by current liabilities.

Source: Data retrieved from Bloomberg and NHH Børsdatabasen.

Elimination: Observations with missing values for current ratio dropped.

Ownership structure hypothesis

Method: The largest shareholder's percentage of the total outstanding stocks and a Herfindahl index of ownership consolidation. The Herfindahl index is defined as the sum of the squared sums of all shareholder voting stocks.

Source: Data retrieved from SNF.

Elimination: Observations with missing values for the largest shareholder's percentage of the total outstanding stocks dropped.

Industry disturbance hypothesis

Method: As described in Section 3.2.

Source: Data retrieved from NHH Børsdatabasen and SDC Platinum.

Elimination: None.

Macroeconomic factors

Method: As described in Section 3.2.

Source: Data retrieved from Bloomberg, SDC Platinum, Wikipedia, the Norwegian Central Bank and the Norwegian Government.

Elimination: None.

Additional adjustments

In addition to the adjustment of outlier observations described above, the observations of the firm, Norsk Hydro, is excluded from the dataset due to uncommonly large values in various years. This was due to the privatization of the company from the Norwegian State.

Table A1 – Targets: Descriptive statistics for the estimation sample

This table provides an overview over the hypothesis promoted by this thesis and the respective variables for the targets in the estimation sample. The data is retrieved from NHH Børsdatabasen, Bloomberg and SNF based on the recorded transactions in SDC Platinum.

Targets					
	No.of obs.	Mean	Std. Dev.	Min	Max
Inefficient management					
1-year sales growth	153	60.927%	239.956%	-57.911%	2454.312%
2-year sales growth	153	18.531%	43.218%	-56.802%	344.088%
EBITDA margin	153	8.534%	34.953%	-178.785%	96.689%
ROE	153	-1.822%	64.039%	-466.349%	225.073%
Asset Turnover	153	0.970	0.686	0.061	3.230
Firm size (NOKm)					
Market Capitalization	153	1,467	2,141	15	13,400
Sales	153	2,193	6,488	4	73,700
Total assets	153	2,671	3,898	12	22,800
Growth resource					
Dummy	153	0.314	0.466	0.000	1.000
Valuation (x)					
PE	153	15.548	48.897	-171.970	414.781
MTB	153	2.155	2.437	-0.049	17.852
Leverage					
Debt to BVE	153	1.280	7.277	-4.306	89.506

Liquidity					
Cash to total capital	153	0.109	0.124	0.003	1.000
Current ratio	153	2.058	4.955	0.063	61.630
Ownership structure					
Largest owner share	153	29.009%	19.714%	2.357%	100.000%
Ownership concentration	153	15.986%	19.436%	0.705%	100.000%
Industry disturbance					
Dummy	153	0.373	0.485	0.000	1.000
Macroeconomic factors					
Brent oil price ($)	153	44.393	29.324	10.940	97.010
10 year Government bond	153	4.918%	1.048%	3.670%	8.120%
Governing party	153	0.150	0.359	0.000	1.000
Aggregated M&A activity	153	22.614	8.744	7.000	40.000

Table A2 – Non-targets: Descriptive statistics for the estimation sample

This table provides an overview over the hypothesis promoted by this thesis and the respective variables for the non-targets in the estimation sample. The data is retrieved from NHH Børsdatabasen, Bloomberg and SNF.

Non-Targets					
	No.of obs.	Mean	Std. Dev.	Min	Max
Inefficient management					
1-year sales growth	2,087	33.710%	167.557%	-78.544%	3579.483%
2-year sales growth	2,087	20.820%	79.436%	-78.690%	1415.663%
EBITDA margin	2,087	7.174%	32.941%	-199.932%	157.663%
ROE	2,087	3.359%	52.669%	-453.813%	637.228%
Asset Turnover	2,087	0.945	0.675	0.005	4.307
Firm size (NOKm)					
Market Capitalization	2,087	5,491	26,000	1	540,000
Sales	2,087	6,337	30,700	2	656,000
Total assets	2,087	7,988	31,200	5	578,000
Growth resource					
Dummy	2,087	0.381	0.486	0.000	1.000
Valuation (x)					
PE	2,087	14.497	51.043	-194.925	495.988
MTB	2,087	2.393	3.267	-8.921	46.039
Leverage					
Debt to BVE	2,087	2.740	137.072	-1729.316	6017.525
Liquidity					
Cash to total capital	2,087	1.137	34.826	0.001	1473.156
Current ratio	2,087	2.219	3.755	0.065	108.624

Ownership structure					
Largest owner share	2,087	28.470%	21.177%	0.849%	100.000%
Ownership concentration	2,087	15.485%	19.771%	0.230%	100.000%
Industry disturbance					
Dummy	2,087	0.300	0.459	0.000	1.000
Macroeconomic factors					
Brent oil price ($)	2,087	39.565	26.763	10.940	97.010
10 year Government bond	2,087	5.201%	1.152%	3.670%	8.120%
Governing party	2,087	0.227	0.419	0.000	1.000
Aggregated M&A activity	2,087	19.942	8.711	7.000	40.000

Table A3 - Correlation matrix for the independent variables in the estimation sample

	1-y sales g	2-y sales g	EBITDA margin	EBIT margin	ROE	Asset turnover	MCAP
1-y sales g	1						
2-y sales g	0.2122	1					
EBITDA margin	0.016	-0.0104	1				
EBIT margin	-0.0346	-0.0354	0.7992	1			
ROE	-0.0073	0.0094	0.3003	0.2875	1		
Asset turnover	-0.09	-0.0794	-0.1025	0.0111	0.0351	1	
MCAP	-0.0178	-0.008	0.0942	0.0664	0.0558	-0.0285	1
Sales	-0.0255	-0.0212	0.0645	0.051	0.0396	0.0261	0.9316
Total assets	-0.0227	-0.0151	0.1016	0.0667	0.0413	-0.0571	0.9418
Grdummy	-0.0344	-0.0049	0.0008	0.0094	-0.0107	-0.0113	0.0626
MTB	0.0153	0.0217	-0.0113	0.0182	-0.0219	0.1481	0.0118
PE	-0.0301	-0.023	0.095	0.0744	0.0712	0.0081	0.0124
PE ind. ad	-0.0343	-0.0223	0.0608	0.0435	0.0221	-0.0335	0.0132
EV/EBITDA	0.0291	0.0156	0.0082	0.0058	0.0244	-0.043	0.0048
EV/EBIT	-0.0259	0.0065	0.02	0.0197	0.0145	0.0259	0.0042
Dis DUMMY	0.0653	0.0608	0.0381	0.0006	-0.0291	-0.2143	0.0699
Debt to BVE	0.001	-0.0005	0.0239	0.019	-0.0077	-0.0183	-0.0024
Debt to MVE	0.0049	0.007	0.0035	0.005	0.0215	-0.0452	0.0044
Cash to total Cp	-0.0026	-0.0056	0.016	0.0125	-0.0169	0.0147	-0.0056
Current ratio	-0.0025	-0.0091	-0.0868	-0.0475	0.0084	-0.1536	-0.0345
Capex/Sales	0.1193	0.0726	0.0927	0.0017	-0.0275	-0.168	-0.0056
Free Float	0.0455	0.0806	0.0006	0.0081	-0.0319	-0.0488	0.0009

	Sales	Total assets	Grdummy	MTB	PE	PE ind.ad	EV/EBITDA
Sales	1						
Total assets	0.9592	1					
Grdummy	0.0598	0.0555	1				
MTB	-0.0212	-0.0408	0.0152	1			
PE	-0.0081	-0.0081	-0.0225	0.1082	1		
PE ind.ad	0.0065	0.0082	-0.013	0.0366	0.6179	1	

EV/EBITDA	0.0018	0.0044	-0.0256	0.0185	-0.0039	-0.0124	1
EV/EBIT	0.0023	0.0024	0.0358	0.0238	-0.0326	-0.0548	-0.1261
Dis DUMMY	0.083	0.0917	-0.0194	-0.0304	-0.0058	0.0363	-0.028
Debt to BVE	-0.0027	-0.0026	-0.0222	-0.0286	0.0001	0.0043	0.1862
Debt to MVE	0.0023	0.0046	-0.0266	0.016	0.0059	0.0013	0.9835
Cash to total Cp	-0.0047	-0.0066	-0.0047	-0.0348	-0.0033	0.0034	-0.4529
Current ratio	-0.0428	-0.0465	0.0291	-0.0135	-0.0133	-0.0124	0.003
Capex/Sales	-0.0189	0.0016	-0.0192	-0.0309	-0.0173	0.1074	-0.0065
Free Float	-0.0172	-0.0074	-0.0693	0.1232	-0.0129	0.0043	0.0727
Current ratio	-0.0428	-0.0465	0.0291	-0.0135	-0.0133	-0.0124	0.003
Capex/Sales	-0.0189	0.0016	-0.0192	-0.0309	-0.0173	0.1074	-0.0065
Free Float	-0.0172	-0.0074	-0.0693	0.1232	-0.0129	0.0043	0.0727

	EV/EBIT	Dis DUMMY	Debt to BVE	Debt to MVE	Cash to total Cp	Current ratio	Capex/Sales
EV/EBIT	1						
Dis DUMMY	0.0035	1					
Debt to BVE	-0.523	-0.0202	1				
Debt to MVE	-0.2388	-0.0312	0.244	1			
Cash to total Cp	-0.34	-0.0008	0.785	-0.409	1		
Current ratio	-0.0028	0.0173	-0.0104	0.0047	-0.0101	1	
Capex/Sales	0.0031	0.0793	0.0001	0.0036	-0.0035	-0.0194	1
Free Float	0.0269	-0.0343	0.0036	0.0718	-0.0425	0.0339	0.0575

	Free Float
Free Float	1

	Brent USD	Brent NOK	USDNOK	10-y bond
Brent USD	1			
Brent NOK	0.9883	1		
USDNOK	-0.6959	-0.6077	1	
10-y bond	-0.6641	-0.6928	0.4587	1

	lnSales	lnMCAP	lntotass
lnSales	1		
lnMCAP	0.7568	1	
lntotass	0.8637	0.8248	1

Table A4 – Targets: Descriptive statistics for the holdout sample

This table provides an overview over the hypothesis promoted by this thesis and the respective variables for the targets in the holdout sample. The data is retrieved from NHH Børsdatabasen, Bloomberg and SNF based on the recorded transactions in SDC Platinum.

Targets					
	No.of obs.	Mean	Std. Dev.	Min	Max
Inefficient management					
1-year sales growth	27	3.035%	34.490%	-71.802%	127.310%
2-year sales growth	27	5.592%	27.630%	-57.773%	91.447%
EBITDA margin	27	22.680%	26.851%	-22.056%	84.356%
ROE	27	3.761%	22.678%	-45.715%	69.876%
Asset Turnover	27	0.752	0.656	0.051	2.051
Firm size (NOKm)					
Market Capitalization	27	1,562	2,074	8	7,746
Sales	27	1,902	2,551	8	12,600
Total assets	27	4,439	5,321	37	16,900
Growth resource					
Dummy	27	0.407	0.501	0.000	1.000
Valuation (x)					
PE	27	-2.558	47.277	-170.622	103.402
MTB	27	1.045	1.583	-0.783	8.239
Leverage					
Debt to BVE	27	0.384	1.980	-8.388	2.291
Liquidity					
Cash to total capital	27	0.079	0.077	0.003	0.300
Current ratio	27	6.677	11.491	0.254	47.964
Ownership structure					
Largest owner share	27	51.162%	37.072%	2.849%	100.000%
Ownership concentration	27	42.672%	40.372%	0.917%	100.000%
Industry disturbance					
Dummy	27	0.296	0.465	0.000	1.000
Macroeconomic factors					
Brent oil price ($)	27	99.187	23.900	55.380	112.980
10 year Government bond	27	2.166%	0.409%	1.590%	3.010%
Governing party	27	0.296	0.465	0.000	1.000
Aggregated M&A activity	27	17.778	6.495	6.000	22.000

Table A5 – Non-targets: Descriptive statistics for the holdout sample

This table provides an overview over the hypothesis promoted by this thesis and the respective variables for the non-targets in the holdout sample. The data is retrieved from NHH Børsdatabasen, Bloomberg and SNF.

Non-Targets					
	No.of obs.	Mean	Std. Dev.	Min	Max
Inefficient management					
1-year sales growth	393	23.681%	116.200%	-75.501%	1642.360%
2-year sales growth	393	33.278%	187.804%	-73.972%	2275.507%
EBITDA margin	393	19.206%	35.606%	-188.748%	164.187%
ROE	393	2.548%	72.075%	-303.871%	808.252%
Asset Turnover	393	0.791	0.584	0.020	4.797
Firm size (NOKm)					
Market Capitalization	393	12,500	49,900	12	469,000
Sales	393	13,300	65,900	3	721,000
Total assets	393	19,900	93,700	16	984,000
Growth resource					
Dummy	393	0.328	0.470	0.000	1.000
Valuation (x)					
PE	393	10.161	37.592	-176.773	325.646
MTB	393	1.828	2.088	-7.895	13.851
Leverage					
Debt to BVE	393	0.528	3.053	-37.524	19.740
Liquidity					
Cash to total capital	393	0.120	0.126	0.006	0.929
Current ratio	393	3.988	4.717	0.022	43.038
Ownership structure					
Largest owner share	393	33.606%	31.927%	0.789%	100.000%
Ownership concentration	393	25.210%	32.944%	0.155%	100.000%
Industry disturbance					
Dummy	393	0.346	0.476	0.000	1.000
Macroeconomic factors					
Brent oil price ($)	393	96.954	23.900	55.380	112.980
10 year Government bond	393	2.302%	0.530%	1.590%	3.010%
Governing party	393	0.517	0.500	0.000	1.000
Aggregated M&A activity	393	16.730	6.330	6.000	22.000

B Takeover prediction model using industry-weighted variables

Table B1 - Prediction models based on industry-weighted independent variables

	Estimates			
Variables (Expected Sign)	Model 1	Model 2	Model 3	Model 4
Return on Equity (-)	1.605 (1.40)	1.575 (1.06)	0.737 (0.23)	1.466 (0.53)
ln[Sales] (-)	0.675* (1.74)	0.681 (1.64)	2.046* (1.91)	1.938** (2.09)
Growth-Resource Mismatch (+)	-0.0353 (-0.05)	-0.0951 (-0.13)	-2.436 (-1.06)	
Price to Earnings (-)	0.00175 (0.38)	0.00135 (0.26)	0.0175 (1.14)	
Market to Book (-)	-0.302 (-1.09)	-0.251 (-0.88)	-0.705 (-0.96)	
Leverage (+)		-0.829 (-1.13)		
Cash to Total Capital (-)		-4.418 (-1.06)	-44.70 (-1.60)	-34.23* (-1.89)
Current Ratio (-)			1.384 (1.33)	1.277* (1.66)
Ownership Concentration (-)			-6.561 (-1.12)	-1.604 (-0.40)
Industry Disturbance Dummy (+)	0.307 (0.50)	0.614 (0.95)		
Industry Disturbance (+)			0.931 (1.49)	1.016* (1.77)
Brent Oil [USD] (+)			-0.0282 (-0.59)	-0.0510 (-1.18)
10 Year Norwegian Bond (-)			-2.196 (-1.44)	-1.505 (-1.23)
Governing Party (+)			1.200 (0.57)	
No. of observations	122	122	78	78
Likelihood ratio Chi^2	9.06	13.36	33.24	30.32
Probability > Chi^2	0.1702	0.1468	0.0016	0.0004
Pseudo R^2	0.1185	0.1747	0.6665	0.6081

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

C Prediction model and investment results excluding natural resources

Table C1 – Fixed effects logit regressions for takeover prediction when excluding natural resources

This table summarize the results from the four different regression models created when natural resources are excluded. Model 1 use firm specific variables proposed by Palepu (1986) and controls for industry disturbance. Model 2 includes additional firm specific variables such as growth, leverage and liquidity to recreate Palepu's final prediction model on the Norwegian market. Model 3 includes a wider set of variables to allow for adjustments based on ownership structure as well as specific factors for the Norwegian market. Model 4 reduces the number of variables to only include the 9 most influential factors.

	Estimates			
Variables (Expected Sign)	Model 1	Model 2	Model 3	Model 4
Growth (-)		-1.454***	-1.238**	-1.184**
		(-3.06)	(-2.44)	(-2.36)
Return on Equity (-)	-0.258	-0.191	-0.243	-0.139
	(-1.14)	(-0.80)	(-0.94)	(-0.51)
ln[Sales] (-)	0.997***	1.347***	0.765**	0.805**
	(4.30)	(4.27)	(2.23)	(2.42)
Growth-Resource Mismatch (+)	-0.332	-0.129	0.0475	
	(-1.32)	(-0.49)	(0.17)	
Price to Earnings (-)	0.003*	0.00330	0.00260	
	(1.65)	(1.61)	(1.19)	
Market to Book (-)	-0.205**	-0.177**	-0.152*	
	(-2.44)	(-2.06)	(-1.80)	
Leverage (+)		-0.0331		
		(-0.45)		
Cash to Total Capital (-)		-3.811**	-5.714***	-6.285***
		(-2.47)	(-3.09)	(-3.50)
Current Ratio (-)			0.102**	0.116**
			(2.02)	(2.34)
Ownership Concentration (-)			-1.343	-1.452*
			(-1.50)	(-1.66)
Industry Disturbance Dummy (+)	0.0508	0.141		
	(0.17)	(0.46)		
Industry Disturbance (+)			0.220*	0.239**
			(1.82)	(2.02)
Brent Oil [USD] (+)			0.0179***	0.0182***
			(2.83)	(3.02)
10 Year Norwegian Bond (-)			-0.533***	-0.527***
			(-3.46)	(-3.53)
Governing Party (+)			-0.107	
			(-0.32)	
No. of observations	805	805	805	805
Likelihood ratio Chi^2	42.01	64.93	102.84	95.75
Probability > Chi^2	0.0000	0.0000	0.0000	0.0000
Pseudo R^2	0.0962	0.1487	0.2355	0.2193

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

Table C2 – Market adjusted return for the two investment strategies when excluding natural resources
This table takes the return generated from the takeover prediction model under the two investment strategies when natural resources are excluded from both the regression and investment strategies, and compares this to the return of the MSCI World Index.

	MXWO	Minimum Misclassifications		Maximum Targets	
		Return	Market Adj.	Return	Market Adj.
2013	24.1%	31.2%	7.1%	16.8%	-7.3%
2014	2.9%	3.2%	0.3%	-1.5%	-4.5%
2015	-2.7%	-3.3%	-0.5%	-4.6%	-1.9%
2016	5.3%	5.0%	-0.3%	2.9%	-2.5%
CAAR 13-16	7.4%	9.0%	1.6%	3.4%	-4.0%
(T-statistics)			(0.42)		-(0.78)

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

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