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The Impact of Target Financial Trends on Bidder Announcement Return

Empirical Evidence from the Norwegian M&A Market

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Preface

This master thesis was written in the spring of 2019 and concludes our Master of Science in Economics and Business Administration at Oslo Business School. The thesis investigates whether trends in accounting-based ratios impact the bidder announcement returns, and present a calculation of percentage change with reference to the variable sample variation, expressed with standard deviation.

We want to extend our gratitude to our supervisor, Einar Belsom, for his guidance, support, knowledge, constructive input, and feedback that have been invaluable in the process of writing this thesis. We also want to thank Per Arne Tufte for his helpful contributions regarding statistical matters.

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Abstract

We study the relationship between bidder announcement return and prior target financial development in the Norwegian takeover market. Based on a sample of 120 acquisitions of primarily private targets, we find that changes in financial ratios relative to the sample standard deviation provide more explanatory power than absolute ratio levels.

Our results indicate that target size and trends in asset turnover have a statistically significant influence on the announcement return. On the one hand, the market is positively related to target size, yet it has a negative development in asset turnover on the other hand. We further find that the impact of the dynamic accounting characteristics is time-dependent, meaning that the importance of these variables changes over time. The trend measure of leverage is significant in the period between 2006-2016, indicating that this variable contributes to explain the announcement return in this particular period. The trend measures of liquidity and net profit margin are, however, not statistically significant in any of the short-term windows.

Reviewing our results, we summarize that the shareholders of the bidding firm are most optimistic about the announcement when the target firm is large in size and with a decreasing asset turnover. In addition, increasing leverage levels seemed to be important in earlier years, whereas trends in liquidity and net profit margin seem to be irrelevant when explaining movements in announcement return regardless of the time frame.

List of Abbreviations

AAR	Average abnormal return
AR	Abnormal return, defined by rate of return on individual target, subtracted by the market rate of return (OSEBX)
AT	Asset turnover, defined by total operating profit divided by average debt and equity
BHAR	Buy-and-hold return
DEBT	Debt-to-equity ratio, defined by total liabilities divided by total equity
LIQ	Liquidity ratio, defined by total current assets divided by total short term debt
NPM	Net profit margin, defined by net profit divided by total revenue
SIZE	Size, defined by total assets of target firm in absolute value

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1 Introduction

Takeovers are highly strategic and complex activities, and the market for mergers and acquisitions (M&As) involves huge transaction values between target and acquiring firms. These activities can be seen as a way to reallocate the resources of the economy (Andrade et al., 2001), and much research has been conducted to reveal whether takeovers create shareholder value. While there has been an extensive amount of research proving that shareholders of target firms experience high gains at the time of a takeover announcement (see, e.g. Andrade et al., 2001), the findings on returns to the shareholders of the bidding firms are more inconclusive (see, e.g. Andrade et al., 2001; Hietala et al., 2003; Eckbo & Thorburn, 2000).

Fuller et al. (2002) suggest that an announcement of a takeover reveals information about numerous things, which makes it hard to explain much of the variation in the acquiring firm's shareholder return. According to Hietala et al. (2003), an announcement will reveal information about the potential synergies from the joining of the firms involved, the target's and the acquiring firm's individual firm value, and how value is split between acquirer and target. They further claim that distinguishing between these factors presents big difficulties that inhibit a clear understanding of the market reaction to an announcement.

Despite these problems, researchers have been able to explain some the variation in abnormal return, including investigating the organizational form of target, size level, and method of payment. The organizational form of the target is proven to affect the returns (see Hansen & Lott, 1996; Chang, 1998; Fuller et al., 2002). Results suggest that acquiring firms, on average, experience loss when announcing a takeover of a public firm, whereas they will profit from announcing a takeover of a private firm or a subsidiary of a public firm. They also find that losses and gains are dependent on the size of the target and method of payment. Moeller et al. (2004) show that acquirer size is negatively related to the announcement return to shareholders of the acquiring firm.

There have, however, been some inconsistencies in the findings concerning the size of the target firm. While some studies show that bidder announcement returns decrease with the relative size of the target (see e.g. Travlos, 1987), other studies report opposite results (see e.g. Asquith et al., 1983). Fuller et al. (2002) find that the impact of relative size on the bidder will depend on whether the target is private, a subsidiary, or public, where size is positively correlated with the bidder announcement return if the target is private or a subsidiary, and negatively correlated in cases with public targets. Myers & Majluf (1984) suggest that firms prefer to pay with stock if management believes that the stock is overvalued; thus a takeover announcement where stock is stated as the method of payment will have a negative impact on the acquiring firm's announcement return. This suggestion has received much empirical support, showing that, at the announcement, cash offers yield greater abnormal returns (see, e.g. Travlos, 1987; Brown & Ryngaert, 1991).

One area of the M&A literature that has received less theoretical and empirical attention is accounting-based measures to gauge M&A performance (Thanos & Papadakis, 2012). To our knowledge, there have not been any studies conducted any which investigate whether the accounting-based measures and ratios of the target firm have any explanatory power when it comes to the stock returns of the acquiring firms when announcing a takeover. It is unclear to us why this is the case, because it is reasonable to assume that such characteristics and features would be of interest to the acquiring firm's shareholders. At the time of the announcement, we expect these shareholders to carefully examine the financial situation of the target in order to understand the implications of the acquisition.

Accounting-based measures are, however, used to a great extent in other parts of the litera-

ture. The prediction of takeover targets is a well-covered part of the M&A literature, where studies aim to reveal the characteristics of acquisition targets (e.g. Dietrich & Sorensen, 1984; Palepu, 1986; Powell, 2001; Brar et al., 2009). These characteristics are often examined by applying accounting-based measures covering, e.g., liquidity, leverage, profitability, growth potential, and size. Beyond explaining the features of increasing or decreasing the probability of an acquisition, target prediction studies help define, to a great extent, the qualities which acquirers value in their targets. We believe that the shareholders of acquiring firms have the same or similar perceptions of desired target qualities. This belief is in accordance with the assumption that management will tend to act in line with the owners' interests. Hence, we assume that the findings in the takeover target prediction literature form a natural basis for the selection of variables that besides can explain the variation of the market reaction to the announcement of a takeover.

The lack of studies examining target characteristics explaining variation in bidder announcement return could be due to challenges that can occur from use of financial ratios (Barnes, 1987), the disadvantages of using accounting-based measures (see, e.g. Thanos & Papadakis, 2012) or due to the absence of meaningful findings or connections. Moreover, Thanos & Papadakis (2012) show that the existing literature on accounting-based measures explaining M&A performance mainly study the financial situation of acquiring firm, whereas less focus is directed towards target firms. They propose that the reason for lack of studies investigating accounting-based ratios for target firms could be that these firms typically are small and medium-sized, and the financial data needed for analyses is unavailable or not published.

Research applying accounting-based measures investigates in many cases the variables in absolute values, often computed as averages over several years. These values express the level of a measure but lack information about the direction of development. We consider development in the targets' financial situation over the final years before an acquisition as important information for shareholders, because it indicates the different financial trends that could influence the prospects of the combined firms. Also, showing the direction of development in an accounting measure can provide us with information about the firm's current situation, potential, or ability to grow. By calculating the percentage change of accounting-based measures, we believe we are able to model how their dynamics impact the announcement returns to acquiring firm's shareholders.

Due to the mathematical nature of financial ratios, the standard calculation of percentage change can lead to extreme values as the denominator will often approach zero. As a result, small changes can seem extremely large. We overcome this issue by applying the variable standard deviation as the reference of the change. This calculation gives us a measure expressing changes in ratios with respect to the variable variation in the sample, rather than a previous level. Thus, our contribution with this study is twofold, in that we aim to both attend to the literature explaining the variation in bidder announcement return, as well as explore an approach expressing changes in accounting measures.

We calculate abnormal returns around the immediate time of announcement for an observation sample, consisting of 120 deals between Norwegian bidder and target firms that were part of a takeover announced between January 1^{th} 2005 and December 31^{th} 2018. Financial ratios are selected based on relevant literature and calculated to express trends. Our chosen variables are applied to explain the variance of bidder announcement returns with regression analyses, and multiple tests are subsequently conducted to evaluate the robustness of our model. A moving window analysis is also performed, in order to map potential time dependency in our variables and to ensure a more nuanced picture of their impact. Potential industry effects are discussed in order to try to explain the detected time dependency, and we suggest that the duality we suspect in our accounting-based measures can also be

explained by these effects. Lastly, we evaluate the inclusion and replacement of variables expressing absolute values in our model.

The remainder of this thesis is organized as follows: In section 2, we present the methodological approach and justification underlying the choice of variables, as well as the dependent variable. Further, in section 3, we describe the process of data collection before we discuss and present the results of the analyses in section 4. Finally, in section 5 we provide a summarized conclusion to our study.

2 Empirical model

We employ an event-study methodology in order to measure the acquiring firm's market reaction to a M&A announcement. The calculation of abnormal returns is on the premise of the market efficiency theory, with an assumption of market rationality saying that an event will immediately be reflected in the stock prices MacKinlay (1997). In section 2.1 we discuss our choice of dependent variable and how we measure the market reaction of a takeover announcement. Further, we continue with justification for our choice of explanatory variables and review how they are computed in section 2.2.

2.1 Dependent variable

The abnormal return of the acquiring firms' stock price around the announcement date is chosen as the dependent variable in order to measure the impact of the takeover and exclude other unrelated movements in prices. We calculate the abnormal return using a buy-and-hold approach to abnormal returns, as is advocated by Lyon et al. (1999) because it expresses the return that the investor actually experiences. The difference between this approach and the other frequently applied calculation, cumulative abnormal return, is, however, very small over short time windows (Fama, 1998).

A short event window is often used when the goal is to capture market reactions and is also used in the literature gauging market reactions to a takeover announcement. Examples of window lengths include 5 days [-2, 2] (Fuller et al., 2002; Goergen & Renneboog, 2004), 3 days [-1,+1] (Andrade et al., 2001; Moeller et al., 2004) and 2 days [-1, 0] (Chang, 1998; Goergen & Renneboog, 2004). Our chosen event window is from the day before the announcement date to the day after the announcement date [-1,1]. Including one day prior to the announcement date will allow us to include possible information leakages, and including one day after the announcement will secure not losing the market reaction after the closing time on the stock exchange (see e.g. Ma et al., 2009; MacKinlay, 1997). In addition, choosing longer event windows, such as several weeks, months, or years, will increase the risk of including further noise in our data, and consequently reduce the accuracy of the study. Andrade et al. (2001, p. 109) state that short-window event studies are "the most statistically reliable evidence on whether mergers create value for shareholders", and further support abnormal return as a suitable method to measure value creation or destruction.

We apply the market adjusted return model, as discussed by Brown & Warner (1980, 1985). The abnormal return is found by subtracting the change in the price of a market index R_m directly from the change in the stock price of each firm R_i, as shown in equation 2.1. The Norwegian Stock Exchange Benchmark Index (OSEBX) is used as the index in this study because it is a representative sample of publicly listed firms on the Oslo Stock Exchange.

$$AR_{i,t} = R_{i,t} - R_{m,t} \tag{2.1}$$

$AR_{i,t}$ denotes the abnormal return of the individual firm i at time t, $R_{i,t}$ is the actual stock return of firm i at time t, and $R_{m,t}$ is the actual return on the OSEBX.

The calculation of $BHAR$ applied in this study is shown in equation 2.2.

$$BHAR_i = \frac{P_{i,t-1} - P_{i,t+1}}{P_{i,t-1}} - \frac{P_{m,t-1} - P_{m,t+1}}{P_{m,t-1}} \tag{2.2}$$

$P_{i,t-1}$ denotes stock price for acquiring firm i the immediate day ahead of the announcement, and $P_{i,t+1}$ expresses the stock price the day after the announcement. $P_{m,t-1}$ is the price of the OSEBX the day ahead of the announcement, and $P_{m,t+1}$ expresses the price of the OSEBX the day after the announcement.

Many studies on bidder announcement return apply the market model to estimate abnormal return (see, e.g., Travlos, 1987; Brown & Ryngaert, 1991; Chang, 1998; Moeller et al., 2004). In addition to the appliance of the market model, Moeller et al. (2004) calculate abnormal return by adjusting for the market return using a value-weighted index. Their results indicate that the estimated abnormal returns are not sensitive to which model is applied. Hansen & Lott (1996) also apply both models to estimate excess return, and find that their results do not statistically differentiate using the two approaches. They suggest that due to lack of stock price data needed for calculations, the estimation of betas actually lead to the exclusion of several observations. Brown & Warner (1980) and Brown & Warner (1985) document that both the market model and marked adjusted return model are well-specified to estimate abnormal returns. According to MacKinlay (1997), one can view the market adjusted return model as a restricted market model. He argues that it should only be used in cases where it is necessary and that the possible bias occurring, due to the restrictions, should be assessed.

A benefit of beta estimation models is that we might achieve more precise measures of the abnormal returns than directly correcting for the market because it takes into account the relationship between the stock and market variation. The difference between the two approaches does not necessarily cause problems unless the differences between the models are caused by impact of the explanatory variables. If this is the case, there might be bias present in the market adjusted return model. This bias will, in turn, have systematic implications for the coefficient estimates. If there is no such correlation, the difference can be considered as "white noise" and the coefficients will be unbiased. However, the differences might lead to higher p-values due to increased standard errors.

There are, however, downsides to the approaches aiming to give a proper beta estimate. Financial literature expresses difficulties when it comes to accurately estimate betas, and the statistical consequences of measuring betas with errors are bias in the slope coefficient and intercept (see, e.g. Bodie et al., 2014). When betas are calculated with historical data to evaluate future values, it can result in estimation errors. This is because changes in capital structures or the fundamentals of a company will lead to changes in betas (Mullins, 1982). Thus, a proxy beta may impact the reliability of the outcome, and we can avoid this by using our approach to directly correct for a market index.

Another concern that we avoid by applying our chosen approach is related to the fact that some of the bidding firms in our sample are recently listed, which limits the amount of adequate data for beta calculations. There might also be extraordinary estimation issues due to limited liquidity. A fraction of the firms in our sample are of smaller size, and newly listed, so they might not experience much stock trading. These liquidity challenges can bias beta estimation.

A number of more sophisticated alternatives for risk estimation have been presented and argued to be better fitted, such as factor models (see, e.g. Fama & French, 1993; Carhart, 1997). If there exist other systematic factors with explanatory power, a one-factor market model might be inadequate. These approaches are, however, time consuming and complex. Additionally, MacKinlay (1997) points out that the gains of such models are limited because each factor has marginal explanatory power, and thus actually reducing the variance to a small extent.

We assume that an announcement of a corporate takeover will give a remarkable reaction in the stock price of the bidding firm. If we further assume that the changes in actual stock return around the time of announcement consist of the reactions to the news and market

movements presented by the index, we believe the reaction to the news will dominate. The market adjusted return model might, therefore, be adequate and provide us with a measure of abnormal return that avoids the potential issues discussed above. Thus, reviewing the costs and benefits of this approach, we find it reasonable to apply the market adjusted return model. Additionally, the short event window helps ensure that the return observed beyond the movements of the index actually stems from the announcement.

2.2 Choice of variables

In order to model the trends of the target firms' financial situation, we calculate the percentage change in different proxies from the three immediate years prior to the announcement. This method reveals the direction of development in different accounting-based measures that we believe would be of importance to acquiring firms' shareholders. We calculate the percentage change with the average variable standard variation over the three years, as the reference of the change. Due to the mathematical nature of financial ratios, their values will in many cases be close to zero. The use of a financial ratio as the reference from which to calculate percentage change is therefore problematic, because it often leads to a denominator with a value close to zero, and therefore can make small changes seem extreme. Using the standard deviation as the reference in the trend calculation is thus more suitable, and provides a measure that captures percentage change with respect to the sample variation. This furthermore ensures that extreme values do not lead to misleading or biased results, as well as controlling for the fact that the variables have differing distributions, making the changes more comparable. This method is employed for all the ratios in our model and is illustrated in equation 2.3.

$$Trend\,calculation = \frac{X_{i,t-3} - X_{i,t-1}}{\overline{STD_m}} \tag{2.3}$$

X_i is the accounting ratio of an individual target firm, $X_{i,t-3}$ is the variable value three fiscal years before the announcement date of the target takeover, X_{t-1} is the variable value one fiscal year before the announcement date, and $\overline{STD_m}$ is the average standard deviation of the individual ratio for all target firms over the three year period.

The selection of variables in this study is based on the extensive literature on firm characteristics of acquisition targets, more specifically the target prediction literature. This is a natural foundation because we assume that acquiring firms and their owners will be concerned with the same financial aspects when they evaluate targets. We further want to ensure that we categorize the financial statement in order to cover its distinctive parts, as well as selecting variables that we believe to be best fitted to measure them in line with relevant literature. This method helps us avoid the problem of statistically "overfitting" our model (Palepu, 1986).

Our main categories are inefficient management (hereunder profitability measure and efficiency measure), financial distress, liquidity, and size. The following section consists of justification of our chosen variables as proxies for their respective hypotheses and discussion of how these measures capture trends.

Inefficient management

Replacement of inefficient management is hypothesized to be a motive for takeovers due to current management's lack of ability to maximize the potential value of a firm. Manne (1965) points out that the performance of a firm is related to the performance of the management, and that takeovers, among several advantages, will help ensure efficient management. This is supported by Jensen & Ruback (1983, p. 44), who suggest that "competing managers who perceive the opportunity to eliminate the inefficiencies can offer target shareholders a

higher-valued alternative than current management while benefiting their own shareholders and themselves".

In line with these assumptions, measures of profitability, growth, and efficiency, are frequently applied in the target prediction literature in order to proxy the hypothesis (see Dietrich & Sorensen, 1984; Palepu, 1986; Ambrose & Megginson, 1992; Powell, 1997; Brar et al., 2009). The findings of this research reveal that both accounting-based measures and market-based measures have discriminatory abilities when it comes to predicting targets. Low asset turnover is found to be an influential variable in the study of Dietrich & Sorensen (1984), despite it not being a statistically significant variable in the study of Brar et al. (2009). The study of Brar et al. (2009) shows additionally that sales growth and operating profit margin have an impact on takeover probability. Dietrich & Sorensen (1984) on the other hand, do not find their measure of profit margin to have discriminatory ability. Related to market-based measures, abnormal return and Tobin's q are shown to have an impact on takeover likelihood (see Palepu, 1986; Brar et al., 2009, respectively).

The varying results discussed above may be partly explained by the fact that various distinctive measures fit under the inefficient management hypothesis, and hence the impact of this hypothesis can be argued to be captured in different manners and measures. In order to cover a broader part of the hypothesis, we include two different measures as proxies, namely profitability and efficiency. Our choices are based on relevant findings that are consistent with our approach to accounting-measures, in order to investigate whether they also can explain variation in bidder announcement returns. We discuss these measures in the following sections.

Net profit margin
Net profit margin (NPM) is a financial ratio that allows us to understand how much profit the target company obtains for each NOK earned in revenue. The level of operating margin can be an indication of future cash flows (Dietrich & Sorensen, 1984). Dietrich & Sorensen (1984) further note that in addition, low margins can indicate large payoffs because new management may see this as an opportunity to achieve higher future cash flows, but low margins may also imply low future cash flows. For this reason, they claim that the expected sign of the variable can be both positive and negative in terms of target likelihood.

In line with the inefficient management hypothesis, a decreasing level of NPM will indicate a reduction in profitability, and thus signal higher potential gains if an acquirer decides to substitute current management. In other words, negative trends in NPM are expected to have a positive impact on bidder announcement returns.

However, as expressed by Dietrich & Sorensen (1984), the levels of the cash flows can also be perceived as an indication about the future levels of cash flows. Brar et al. (2009) find evidence that target firms actually have higher operating profit margins than firms not being bought. Hence, increasing NPM can also result in an augmentation of the bidder announcement return. In keeping with the finding of Brar et al. (2009), we hypothesize that a measure which considers the direction of development can give a stronger indication about the prospects of the financial measure, compared to that which the average of the past observed levels convey. The assumption that higher levels of net profit margin have a positive impact on the bidder announcement returns challenges the hypothesis of inefficient management, and indicates that acquiring firms are interested in buying firms that are more profitable. This may be because there are many complex and unclear reasons why a firm experiences low or decreasing profitability, while the takeover of a firm with high or increasing levels of profitability can be considered safer.

Because NPM has shown different results in terms of its impact on target likelihood, we find it interesting to examine whether the direction of development can be of importance when it comes to explaining bidder announcement returns. To calculate the NPM-ratio, we divide the net profit with the total revenue as seen in equation 2.4.

$$NPM = \frac{Net\,profit}{Total\,revenue} \tag{2.4}$$

Net profit consists, more precisely, of total revenue minus total expenses of the target company, and total revenue includes both the operating and financial income of the target company. In order to measure the dynamic effects over a three year period, we calculate the percentage change of the NPM between one fiscal year ahead of the announcement $(t-1)$ and three fiscal years ahead of the announcement $(t-3)$.

Asset turnover
We choose asset turnover (AT) as the measure of efficiency. According to Dietrich & Sorensen (1984), there is a relationship between low asset turnover and inefficient use of assets. A low level can indicate that big investments have failed to induce sufficient sales growth. The acquiring company can see this as an opportunity if the reason for low asset turnover is poor management. The study of Dietrich & Sorensen (1984) confirms this hypothesis, and shows that lower asset turnover increases the chance of becoming a takeover candidate. It is natural to further assume that such information will be of interest to the shareholders of the acquiring firm. Moreover, changes in the AT measure the years before the announcement will contain important information about the target's financial situation, which is of interest for the acquiring firm's shareholders.

In line with the efficient management hypothesis, we assume that a negative development of this efficiency measure will have a positive impact on the stock return of acquiring firms. We investigate this by calculating the percentage change from three years before the announcement date to the year previous to the announcement date. AT is calculated by dividing the operating profit by the average sum of debt and equity over the period. The calculation of the measure is shown in equation 2.5 below.

$$AT = \frac{Total\,operating\,profit}{(SED_t + SED_{t-1})/2} \tag{2.5}$$

SED_t is the sum of debt and equity of the target firm in the current year, and SED_{t-1} is the sum of debt and equity of the target firm in the previous year. We calculate the percentage change over the three fiscal years prior to the announcement.

Financial distress

Leverage level as a motive for M&As is frequently discussed in financial literature. This hypothesis is based on the fact that targets are expected to be in financially distress, with higher debt levels. A high leverage level may indicate two different aspects for the acquiring firm. Firstly, it can give tax saving opportunities and reduced cost of capital. Secondly, higher leverage levels increase the likelihood of bankruptcies (Powell & Yawson, 2007). On the other hand, a low debt ratio may indicate that the potential debt capacity is not fully utilized, which can be considered attractive for the acquiring firm (Dietrich & Sorensen, 1984; Hasbrouck, 1985; Song & Walkling, 1993). This is documented by Palepu (1986) who finds statistical evidence that leverage has discriminatory ability, and that leverage is negatively related to the probability of becoming a target.

We believe shareholders of acquiring firms are concerned with changes in the capital structure of the target firm. As discussed, different leverage situations can be perceived as both positive and negative. This duality creates an ambiguous expectation of how changes in

debt the years ahead of an announcement year will affect the market reaction, and can lead to both a positive and negative coefficient sign. We use the debt-to-equity ratio to calculate the leverage level ($DEBT$), which is a reasonable measure to evaluate a target's financial structure. The formula is shown in equation 2.6 below.

$$DEBT = \frac{Total\ liabilities}{Total\ equity} \tag{2.6}$$

To measure the change in leverage over time, the percentage change is calculated over the three fiscal years ahead of the announcement at time t.

Liquidity

Hasbrouck (1985) discusses how the role of liquidity measures in connection with takeover activity can be challenging to interpret, e.g. in relation to that there are a number of reasons as to why a firm may hold excess cash or other liquid financial assets. Castagna & Matolcsy (1985) suggest that poor management can lead to lower liquidity levels, and that illiquidity and inefficiency make firms more vulnerable to takeovers. These thoughts illustrate how liquidity hypothesis can also fit under the hypothesis that firms in financial distress are more likely targets. On the other hand, Dietrich & Sorensen (1984) hypothesize that a high current ratio may signal that asset allocation is not efficient, that the firm has unused debt capacity, and that the firm has excess liquidity. The latter explanation is also in line with the causal link between large cash reserves and adverse management behavior as discussed by e.g. Jensen (1996) and Harford (1999). Song & Walkling (1993) and Dietrich & Sorensen (1984) also point to that high liquidity may create opportunities for acquiring firms, in that the acquisition can be financed partly by the target's cash reserves, which they believe make targets more susceptible to takeovers.

The impact of liquidity in target prediction has been carefully examined. Brar et al. (2009) find statistically significant evidence that targets have lower cash-to-capital levels than their non-acquired counterparts, in line with the hypothesis presented by Castagna & Matolcsy (1985). The finding that liquidity measures have discriminatory ability is also found in the studies of e.g. Hasbrouck (1985) and Harford (1999). In the study conducted by Harford (1999), the variable expressing liquidity also shows a negative sign, expressing that lower liquidity increases the likelihood of becoming a takeover target. He suggests that firms with higher cash levels may be better fitted to defend themselves during takeover attempts. Other studies, however, fail to show that liquidity can help predict targets (see e.g. Palepu, 1986; Dietrich & Sorensen, 1984; Castagna & Matolcsy, 1985; Song & Walkling, 1993). Harford (1999) proposes an explanation to these differing results, suggesting that liquidity is defined in various manners, and additionally argues that the latter studies do not control for differences that influence what is to be seen as normal cash level in a specific industry or at a specific time.

Due to these diverging hypotheses and findings, we find it particularly interesting to investigate whether liquidity as an accounting measure has explanatory power on bidder announcement return, and also whether the dynamics of the liquidity measure can capture anything beyond what a static level can. Based on the review of earlier findings, we expect that a negative trend in liquidity will have a positive impact on bidder announcement returns. This assumption is in line with the hypothesis and findings of Harford (1999), in that we expect target firms to be in gradually poorer condition to defend themselves as the liquidity levels decrease.

We choose current ratio as a proxy for liquidity. The calculation is as follows:

$$LIQ = \frac{Total\ current\ assets}{Total\ short\ term\ debt} \tag{2.7}$$

Similar to the previous variables, we calculate the percentage change over the three years prior to the announcement year, in order to capture the dynamic effects of the leverage ratio.

Firm size

We include firm size as a control variable in this study. Several studies show that the probability of becoming a takeover target is negatively correlated with target size (e.g. Brar et al., 2009; Palepu, 1986; Ambrose & Megginson, 1992). Palepu (1986) propose that this is because of size-related transaction costs, including those related to targets adjusting to acquiring firms' organizational structures or how fitted targets are to defend themselves. In addition, he suggests that firm size will be negatively correlated with the number of potential bidders. These thoughts and findings are supported by Hasbrouck (1985), Ambrose & Megginson (1992) and Brar et al. (2009), among others. Based on these findings, it is natural to assume that a target's size will be conceived the same way as by the acquiring firm's shareholders.

Studies conducted on bidder announcement return do, however, show a more nuanced picture. Fuller et al. (2002) find that in the case of transactions of private firms or subsidiaries of public firms, the size of the target has a positive effect on the market reaction, increasing the return of the acquiring firm. Fuller et al. (2002) propose that an explanation for these findings can be that nonpublic firms are less liquid than their public counterparts, due to the fact that buying and selling them is more complicated. Because of this, they suggest that this results in a discount when purchasing a nonpublic firm compared to one that is public because their lower liquidity makes them less attractive. Because our data sample consists mainly of acquisitions of private firms, we expect to observe a similar effect in our study.

We choose the target's total book assets as the measure of size to test this hypothesis. This measure has also been used to measure size in other studies (see e.g. Palepu, 1986; Powell, 2001). The variable is measured as an absolute value in the target's financial statement in the last fiscal year prior to the deal announcement and is expressed in billions. Thus, this control variable expresses an absolute level, unlike the remaining explanatory variables that express change.

3 Data

The sample of acquisitions and mergers come from Thomson Reuters Eikon. We select deals with announcement dates between January 1^{st} 2006 and December 31^{th} 2018. Stock prices are collected from Thomson Reuters Datastream, and index prices are retrieved from Oslo Børs.

In order to be included in the sample, the following criteria must be satisfied:

I Both parties in the deal are Norwegian firms.

II The acquiring firm is listed on either Oslo Stock Exchange or Oslo Axess Stock Exchange at the time of the announcement.

III The deal status is listed as "Completed", meaning that the deal is accepted by both parties and that it is announced as completed.

IV The acquiring firm ends up with all the target shares after the deal, which results with a percentage stake of 100%.

These restrictions gave us a sample of 231 deals.

Financial statements and accounting information were extracted from Proff Forvalt's database. Observations of which it was not possible to obtain financial statements for two or three years ahead of the announcement year were removed from the sample. We accept cases where there are two years of financial statement, for example, if the firm was founded two years ahead of the announcement because that still provides us with the possibility to calculate percentage change and thus allows us to investigate the development in accounting-ratios. If a firm announced several acquisitions in one day, these deals were dropped from the sample, because it is impossible to fully isolate the effect each target has on the abnormal return. Including these observations could, therefore, cause the results to be erroneous. These choices concerning exclusions of problematic observations results in a total sample of 122 M&A deals where the target firms included in the study are mainly private.

Based on this sample, we further apply the Cook's Distance (CD) approach in order to identify and remove extreme observations that may negatively impact the regression results. There have been suggested several numerical cutoffs concerning influential observations (Fox, 1991). Fox (1991) points to that it is risky to use absolute values such as 1 as cutoffs because it can lead to the loss of data that is influential, and further propose $D_j > 4/(n-k-1)$ as a potential cutoff measure. This cutoff is calculated to be 0.035. Six of our sample observations exceed the cutoff. Two of them stand out with values of 2.21 and 1.01, compared to the remaining with values lower than 0.15. Because of our limited sample, we strive to keep as many observations as possible. Since the two biggest observations are above the cutoff value, in addition to exceeding the rest substantially, we exclude them and keep the remaining four in the sample. This leaves us with a total of 120 observations.

Some firms in the sample report their financial statements in other currencies such as United States dollar (USD) or euro (EUR). In these cases, we converted the numbers concerned using historical exchange rates provided by Norges Bank.

Other studies applying financial ratios in their analyses, like the target prediction literature, often exclude financial firms from their samples. This is because these firms may disrupt or bias the results, in that their financial ratios have to be interpreted differently. We do not experience big changes in results by excluding such firms in our study, and thus decide to keep them to ensure a more correct image of the market as a whole in our study.

Table 1 shows an average announcement return (AAR) of 2,22% for the total sample period. This result differs from the findings in Andrade et al. (2001) which show that average bidder returns are small and negative, in line with the results of e.g. Mulherin & Boone (2000) who show a low negative but statistically insignificant effect on bidder return. Other studies show small positive or zero abnormal return at announcement (see, e.g., Eckbo & Thorburn, 2000).

Table 1: Average abnormal return sorted by year

Year	Number of deals	AAR	t-Statistic
2018	4 (3.3%)	1.58%	2.66^a
2017	10 (8.2%)	7.32%	2.52^b
2016	3 (2.5%)	5.35%	0.77
2015	6 (5.0%)	-3.43%	-2.58^b
2014	8 (6.7%)	5.83%	2.33^b
2013	5 (4.2%)	-0.37%	-1.34
2012	5 (4.2%)	-0.22%	-0.25
2011	8 (6.7%)	1.86%	2.32^b
2010	12 (10.0%)	1.85%	1.23
2009	7 (5.8%)	-0.11%	-0.08
2008	6 (5.0%)	4.74%	2.93^a
2007	21 (17.5%)	2.45%	2.74^a
2006	12 (10.0%)	2.04%	0.93
2005	16 (13.3%)	1.13%	1.27
Total	120 (100%)	2.22%	4.35^a

^{a} denotes significance at 1% level.
^{b} denotes significance at 5% level.

Because our sample consists essentially of private target firms, the positive abnormal return found in this study is in line with the results of e.g. Fuller et al. (2002) and Chang (1998), and thus our study contributes as a further support to their findings in that acquiring private firms yield positive and significant abnormal returns.

As table 1 shows, *AARs* vary over the years in the sample period, but are mainly positive. We calculate a t-test, to check whether abnormal return is statistically significantly different from zero. The t-test is conducted as shown in equations 3.1 and 3.2, and reported in table 1.

$$t = \frac{\bar{x} - 0}{s_{\bar{x}}} \tag{3.1}$$

$\bar{x}$ denotes the sample mean, n is the sample size, s is the sample standard deviation, and $s_{\bar{x}}$ denotes the estimated standard error of the mean, calculated as shown in equation 3.2.

$$s_{\bar{x}} = \frac{s}{\sqrt{n}} \tag{3.2}$$

About half of the yearly average abnormal returns through the sample period is statistically significantly different from zero at the 1% or 5% level. The highest observed average abnormal return through the sample period is from 2017, statistically significant on the 5% level. Only one of the four yearly negative announcement returns in our sample period is significant, which is the yearly return of 2015, also the year with the lowest observed average abnormal return. The average abnormal return of the total sample is significant at the 1% significance level. Thus, we can reject the null hypothesis and conclude that shareholders of acquiring firms of our sample on average gain positive abnormal returns at the announcement of takeovers.

Moreover, the table shows that a greater share of the deal announcements is in the first half of the sample period, also visualized in figure 3.1. This is consistent with the sixth global merger wave, examined by Alexandridis et al. (2012), among others, that they suggest lasted from 2003 to approximately the end of 2007.

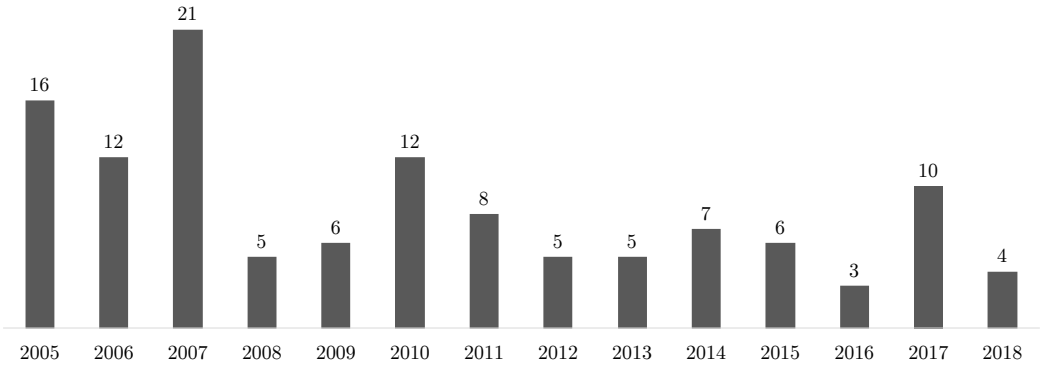

Figure 3.1: Sample over the estimation period, as shown in table 1

Thomson Reuters categorize all firms in their database, and our target and acquiring firms are sorted in respectively 39 and 31 different industry categories. With a data sample of 120, this leads to few observations in each category. The ten most frequent industries for both target and acquiring firms are reported in table 2.

The acquiring firms are more concentrated with respect to the industry than target firms. Table 2 shows that 66.7% of all targets in our sample are included in the ten most frequent industries, leading to that the remaining 33.3% is distributed in the 29 other categories. For acquiring firms, the equivalent is 75.0% in the ten most frequent, leaving 25.0% of the firms in the 21 remaining industry categories. This results in many industry categories only consisting of one firm in our sample.

The most frequent industries in the sample are very similar for target and acquiring firms. Around 20% of both types of firms are from the "IT Consulting & Services" industry, making it the most frequent industry, containing twice as many firms as the industry in second place.

Table 2: Ten most frequent industries of the sample

Industry of target firms	N	Industry of acquiring firms	N
IT Consulting & Services	23 (19.2%)	IT Consulting & Services	27 (22.5%)
Building/Construction	12 (10.0%)	Oil & Gas	13 (10.8%)
Oil & Gas	8 (6.7%)	Building/Construction	11 (9.2%)
Transportation & Infrastructure	8 (6.7%)	Transportation & Infrastructure	8 (6.7%)
Agriculture & Livestock	7 (5.8%)	Machinery	6 (5.0%)
Other Industrials	5 (4.2%)	Agriculture & Livestock	5 (4.2%)
Professional Services	5 (4.2%)	Food and Beverage	5 (4.2%)
Food and Beverage	4 (3.3%)	Internet Software	5 (4.2%)
Machinery	4 (3.3%)	Other Industrials	5 (4.2%)
Wireless	4 (3.3%)	Professional Services	5 (4.2%)
Sum	80 (66.7%)	Sum	90 (75.0%)

Table 3 reports descriptive statistics and shows that an average takeover target in this sample has total assets of NOK 0.774 billion the last fiscal year prior to the announcement.

It further reports that average targets have increased asset turnover, debt-to-equity, and liquidity over the three years before the announcement, whereas net profit margin over the same period has decreased. The variables NPM and $DEBT$ stands out with a considerably higher average percentage change with respectively -14.01% and 12.38%, while AT on average increase 0.03% and LIQ on average increase 5.99%. AT has lower standard deviations, confirming that a majority of reported values are closer to the mean for this variable than in the cases of NPM, $DEBT$ and LIQ, which also reports the most extreme minimum and maximum values of the variables expressing trends.

The control variable, $SIZE$, is the only variable not intended to express change. The minimum and maximum values of the $SIZE$ variable show that there is an extreme difference between the smallest and the biggest target firm. We can see from the mean and median values that the variable is positively skewed and long-tailed.

Table 3: Descriptive statistics

Variable	Mean	St.Dev	Median	Max	Min
SIZE*	0.7738	2.9196	0.0460	0.0004	23.5368
NPM	-0.1401	0.9907	-0.0008	-7.9609	2.6119
AT	-0.0003	0.5504	0.0000	-2.4890	2.6446
DEBT	0.1238	1.4146	-0.0142	-3.5105	12.8566
LIQ	0.0599	1.3249	0.0000	-3.0258	11.2316

* Expressed in billions (10^9).

The median of both the LIQ and AT variable are zero. In the case of LIQ, this is either because there is no change in the three years, or that changes from year -3 to -2 reverts back to where it originated in year -3. In the case of AT, the zero occurs because a few of the target companies do not have operating income three years before the announcement, which leads to zero asset turnover and thus to no change in the financial ratio.

4 Empirical analysis

In this section we present our empirical analyses and results. We begin by discussing the regression results of our main model in part 4.1, followed by results from robustness tests of the model in part 4.2. Next, in part 4.3 we look into how the impact of these variables change over time, and continue with a discussion of possible industry effects in part 4.4. Further, we compare our main model with models excluding some of the variables in part 4.5, and finally, we extend our analysis in part 4.6 by testing regressions with absolute values of our chosen financial ratios, and compare these with the results of the regressions including mainly trend variables.

Table 4: Explanatory variables and expected impact on abnormal return

Hypothesis	Variable	Expected sign
Inefficient management	Net profit margin	$+/-$
	Asset turnover	$-$
Financial distress	Debt-to-equity ratio	$+/-$
Liquidity	Current ratio	$-$
Target size	Total assets	$+$

Table 4 gives an overview of our hypotheses, their respective variables, and the signs we expect to observe in our study as discussed in chapter 2.

4.1 Discussion and analysis

The regression analysis presented in table 5 shows the results of our main model, consisting of the variables presented in table 4. It consists of three significant variables, including the intercept. The control variable $SIZE$ and the change ratio AT are significant at respectively 1% and 5% significance level, and we can thus reject the null hypothesis that there is no relationship between AT and $SIZE$ and the abnormal returns from a takeover announcement.

Table 5: Regression analysis of the main model

Variable	Coefficients	Standard error	p-values
Intercept	0.018	0.005	0.000^a
SIZE	0.007	0.002	0.000^a
NPM	0.007	0.006	0.213
AT	-0.022	0.009	0.013^b
DEBT	0.003	0.004	0.452
LIQ	-0.003	0.004	0.364
N	120		
R-squared	0.183		
Standard error	0.052		
F-statistics	5.111^a		

^{a} denotes significance at the 1% level.
^{b} denotes significance at the 5% level.

Judging by the regression coefficients, the greatest determinant in the regression is the asset turnover (AT) variable, which is negatively loaded and thus in line with our hypothesis that target management's inefficient use of assets may be seen as an attractive opportunity to shareholders. More specifically, the result can be interpreted as the shareholders of acquiring firms are concerned with the direction of development in AT. As shown in table 5, an increase of one standard deviation in the AT variable, results in a decrease of -2.2% in the

abnormal return, ceteris paribus.

Our result concerning AT is in accordance with the findings of Dietrich & Sorensen (1984). They find that lower AT increases the probability for a target to become a takeover candidate, which further supports our hypothesis that both the shareholders of acquiring firms and the management are concerned with the same features in a target firm.

The second variable with a statistically significant relationship to the dependent variable is the absolute size of the target firm ($SIZE$). The regression shows that for every billion NOK increase in target total assets, bidder's abnormal returns increase with 0.7 percent, controlled for the other variables in the regression. As reviewed in chapter 3, our sample consists mainly of private target firms. The positive correlation observed between size and abnormal return is, as expected, consistent with the research of Fuller et al. (2002). Our results consequently provide further support to their findings, in that we document that acquisitions of private firms yield positive returns.

The net profit margin (NPM) variable and debt-to-equity ($DEBT$) have both positive regression coefficients, but none of them are statistically significant with p-values of 0.213 and 0.452 respectively. The positive coefficient of NPM contradicts the expected result in regard to the inefficient management hypothesis, but is consistent with the expectation that increasing NPM has a positive impact on bidder announcement returns. Furthermore, the positive relationship is in line with the results of Brar et al. (2009), which further supports the assumption that management and shareholders have aligned perceptions of target features. Moreover, with a relatively low p-value of 0.213, we cannot exclude the possibility that the influence of this profitability measure is of importance to shareholders of the bidding firms.

The finding that NPM did not have a statistically significant effect may be due to the duality of the measure, in that it may impact bidder announcement return in both directions. As reviewed in section 2.2, increasing levels of NPM may indicate growth and much upside potential for bidding firms, while a decrease of profitability may be perceived as an opportunity to replace inefficient management. The way in which an increase or decrease is perceived may, however, be dependent on different industries or deal categories. Thus, on average the proxy might not have a clear impact due to the opposing effects of the measure.

As for our hypothesis of financial distress and the $DEBT$ variable, the positive sign of the coefficient signals that shareholders of bidding firms may be more concerned with increasing tax saving opportunities and increasingly financially distressed targets than they are with exploiting unused debt capacity. The $DEBT$ variable also show similar results to those in the target prediction literature, e.g. Hasbrouck (1985) and Dietrich & Sorensen (1984), however, both of these studies fail to document a statistically significant relationship. As mentioned, the p-value of the $DEBT$ variable is 0.452, indicating that we cannot document a clear relationship between this variable and the bidder abnormal return in this study either.

Although $DEBT$ is not statistically significant in our main model over the total sample period, we detect an impact of the proxy in certain time windows with a moving windows approach, reviewed and discussed in section 4.3. As with the NPM variable, the duality of the $DEBT$ measure is a possible reason why the measure is not statistically significant. In the analysis in section 4.3, we observe that the variable coefficient sign also changes to some degree, depending on which years are included. A possible explanation could be that the perception of an increase or decrease of a specific variable is time-dependent, e.g., due to more frequent takeovers in certain industries in certain time periods.

Finally, table 5 shows a negative coefficient for the variable expressing changes in liquidity (LIQ), which indicates that decreasing levels of liquidity in a target firm are perceived positively by shareholders of the bidding firms. The variable is not statistically significant with a p-value of 0.364. As with the other variables, LIQ does however provide some support to the prediction that owners and management have similar interests concerning target characteristics, since the sign from our regression is in line with the results of, e.g., Harford (1999).

Judging by this variable's p-value, the measure cannot, however, be said to have substantial explanatory power when it comes to the bidder announcement returns. A possible explanation, as for NPM and $DEBT$, is the inherent duality of the variable. There are positive sides to both high and low levels of liquidity, which can make development in either direction, both favorable and unfavorable. As discussed previously, how distinctive industries and firms with specific characteristics interpret the direction of development may vary. Because of this, it is possible that the variable on average seems like it does not have any impact on the dependent variable, but it does not necessarily mean that the effects are nonexistent. This possible explanation is in line with the one proposed by Harford (1999) to why few have shown significant relationships to liquidity measures. He suggests that the levels of liquidity will depend on the industry so that studies should correct for industries in order to model the effects of the measure. In our main model, we do not correct for industries, but doing so may give other results.

Continuing to the model summary, the R^2 reports that the model explains 18.3% of the sample variation. The relatively low explanatory power is a natural outcome in regressions aiming to explain returns to acquiring firms. Accounting information is only one of many factors to consider, and many conditions that might affect the bidder returns are not included in the regression. The low explanatory power, along with positive and significant F-statistic, is in line with other studies on returns to acquiring firms (see, e.g., Chang, 1998; Fuller et al., 2002).

4.2 Robustness tests of the main model

In order to check whether the main model is robust, we conduct several different robustness tests.

Testing for multicollinearity
We test for any worrying correlations between the independent variables in the model by examining the correlation matrix of the main model presented in table 6.

Table 6: Correlation matrix and the variation inflation factor (VIF)

	SIZE	NPM	AT	DEBT	LIQ
SIZE	1.00				
NPM	-0.02	1.00			
AT	-0.04	0.05	1.00		
DEBT	0.03	-0.55	-0.10	1.00	
LIQ	-0.01	0.15	-0.03	-0.18	1.00
VIF	1.00	1.43	1.01	1.46	1.04

The strongest relationship is between the variables NPM and $DEBT$, with a negatively loaded correlation of -0.55. The value is not worryingly high, but to be certain of this evaluation, we run the variation inflation factor (VIF) test shown in the bottom of table 6. The VIF helps ensure that the correlation found between the independent variables will not lead to misleading results in the regression analysis. The results are reassuring, showing low VIF values that support the results of the correlation matrix. Thus, we cannot detect any

problematic multicollinearity in the model.

Testing for heteroscedasticity
When plotting the residuals of our main model, we notice that the pattern seems fan-shaped, which indicates that our model might be heteroscedastic. The residual plot is shown in figure 4.1.

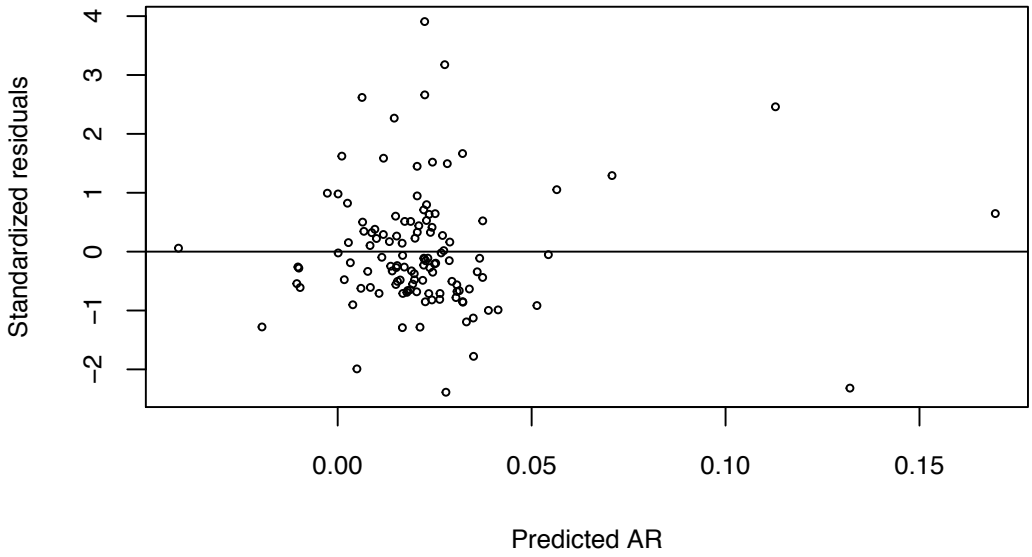

Figure 4.1: Residual plot of the main model, showing sign of a fan-shaped pattern, calculated and plotted in R

To further evaluate whether the standard errors are non-constant, we run two tests to measure the presence of heteroscedasticity. First, we run the Breusch-Pagan-Godfrey test with the null hypothesis of the error variances being all equal. Second, we run White's test with a similar null hypothesis, except for the exclusion of cross-terms and squared variables. The p-values of the F-tests are 0.617 and 0.238 respectively, both far from significant. Thus, we fail to reject the null hypothesis, and we can assume homoscedasticity in our model.

Testing for specification error
To investigate whether our model is correctly specified, we run the standard Ramsey RESET test that measures the existence of neglected non-linearities in the model. The null hypothesis states that the model is correctly specified. The p-value of the unrestricted model is 0.672, and we cannot detect any apparent non-linearity in the model. Thus, we fail to reject the null hypothesis and conclude that there is no evidence of misspecification of functional form.

Testing with bootstrap
In order to investigate whether our regression results are coincidental and that the sample data is weak, one can treat the sample data as the population, from which the bootstrap technique is used to recreate samples (Chernick & LaBudde, 2011). The number of recreated samples varies, but choosing 1000 samples or more is preferable in order to ensure that the result of the bootstrap is robust (Davison & Hinkley, 1997). Based on this, we choose to recreate the regression of the main model with 5000 new samples using the bias-corrected method (as in e.g., MacKinnon et al., 2004; Preacher & Hayes, 2004). This method reduces the bias in the standard errors by minimizing the impact of the regression assumptions. This likely makes the results from the bootstrap technique more trustworthy than the results of

the original model.

In order to compare the bootstrap with the original model, we recreate the regression including confidence intervals and bias estimates. The "Lower" and "Upper" terms stand for the lower and upper values of the confidence intervals. The results of the original model are shown at the top of table 7, followed by the bootstrap regression at the bottom.

Table 7: Results of the main model including 95% *confidence intervals, followed by the results of bootstrapping with* 5000 *recreated samples*

	Coefficients	SE	Bias	p-value	Lower	Upper
Intercept	0.018	0.005	–	0.000[a]	0.008	0.028
SIZE	0.007	0.002	–	0.000[a]	0.003	0.010
NPM	0.007	0.006	–	0.213	-0.004	0.019
AT	-0.022	0.009	–	0.013[b]	-0.039	-0.005
DEBT	0.003	0.004	–	0.452	-0.005	0.011
LIQ	-0.003	0.004	–	0.364	-0.011	0.004

	Coefficients	SE	Bias	p-value	Lower	Upper
Intercept	0.018	0.005	0.000	0.000[a]	0.009	0.028
SIZE	0.007	0.004	0.000	0.013[b]	-0.001	0.013
NPM	0.007	0.007	-0.001	0.147	-0.007	0.019
AT	-0.022	0.007	0.001	0.004[a]	-0.034	-0.005
DEBT	0.003	0.007	0.000	0.547	-0.014	0.016
LIQ	-0.003	0.006	0.002	0.354	-0.009	0.016

Note: Standard error is expressed as SE.
[a] denotes significance at 1% level.
[b] denotes significance at 5% level.

Comparing the two regressions, we see that the bootstrap is approximately equal to the results of the main model. The greatest differences lie in the change of $DEBT$ between the two regressions, but with no estimated bias in the respective variables. The standard errors from the bootstrap are close to the values of the main model, which are supported by the very small bias estimates. Further, we notice some greater differences in the confidence intervals, however, these are not substantial and can be influenced by the large dispersion of the observation values. Finally, when looking at the p-values of the bootstrap, both the $SIZE$ and AT variables are statistically significant, as they are in the main model. In conclusion, the similarities of the results are reassuring, showing no sign of problematic differences between the two regressions.

4.3 Impact of variables in different periods of time

To get a more nuanced picture of the impact of financial ratio trends, we extend our study by examining different time windows within our main time frame. A moving window approach allows us to investigate possible time differences in the impact of our chosen variables, as well as further checking the robustness of the study. We split our time series into 31 shorter time windows with a minimum of 52 observations, and run the main model on each window. As we expand the time window one year at a time, we are able to observe whether specific years influence which variables that have an impact.

These regressions reveal differences in terms of which variables are having explanatory power on the bidder announcement returns over the different time windows. This finding is interesting because it proves and illustrates that the features shareholders consider important are time-dependent. An overview of variables of impact in the different time windows is

presented in table 9. We believe the reasons behind these shifts of explanatory power are complex, and that that they are affected by many different aspects. One explanation is merger waves, as these waves also explain and identify shifts in M&A behavior/attention. As mentioned in chapter 3, the last named merger wave is the sixth. This study examines a time period that exceeds this merger wave by ten years, and thus this study contributes to this literature because it highlights new areas of importance in the current situation of M&A activity in Norway. The potential industry effects discussed in section 4.1 might also be one of the reasons for the varying results over time. We hypothesize that certain periods of time might be more heavily weighted with certain industries than others. Industry effects are more thoroughly discussed in section 4.4.

Table 8 shows the results of a time window from 2007 to 2016, illustrating that variable responses differ over time. In this time window, $DEBT$ is statistically significant at the 5% level, in contrast to the results over the entire time span, as shown in table 5. An increase of one standard deviation in $DEBT$ results in an increase of 1.2% in the abnormal return, ceteris paribus, in the period of 2007-2016. The $DEBT$ measure is also the second most influential variable in this window, after AT.

Table 8: Regression analysis in time window 2007-2016 as shown in table 9

Variable	Coefficients	Standard error	p-values
Intercept	0.014	0.005	0.009^a
SIZE	0.005	0.001	0.001^a
NPM	0.004	0.005	0.363
AT	-0.026	0.010	0.011^b
DEBT	0.012	0.006	0.034^b
LIQ	-0.005	0.004	0.199
N	78		
R-squared	0.278		
Standard error	0.043		
F-statistics	5.540^a		

^{a} denotes significance at the 1% level.
^{b} denotes significance at the 5% level.

Similar to the main model over the total time frame, the two variables $SIZE$ and AT are statistically significant in the window presented in table 8. However, only the intercept and AT are statistically significant for almost all of the shorter time windows, as shown in table 9. The AT variable is, however, not significant in the time windows excluding years before 2008, which indicates that the variable may have more explanatory power towards the first part of the entire time span. The $SIZE$ variable, in turn, tends to have more explanatory power towards the latter part of the time span of our study. These findings indicate that both the AT and $SIZE$ variables are robust in that they have been of importance over large parts of the total time period. To elaborate, over a total of 31 time windows, the $SIZE$ and AT variables are statistically significant in 14 and 23 periods, respectively. However, the focus on AT and $SIZE$ variables seem to be more significant in particular periods of time.

All the regressions in table 9 report a negative coefficient for the AT variable, supporting the underlying hypothesis of inefficient management, as discussed in section 4.1. The sign of the $SIZE$ variable, on the other hand, varies. Three of the 31 total time windows show a negative $SIZE$ coefficient, in contrast to what we observe in our main model over the entire time span. None of the regressions including a negative $SIZE$ measure is, however, statistically significant.

Table 9 shows that the $DEBT$ variable is found to be statistically significant in several of the

Table 9: Statistically significance of variables in shorter time windows

	N	Intercept	SIZE	NPM	AT	DEBT	LIQ
Start year 2005							
2005-2009	60	$+^{a}$	$-$	$-$	$-^{b}$	$-$	$-$
2005-2010	72	$+^{a}$	$+$	$-$	$-^{b}$	$-$	$-$
2005-2011	80	$+^{a}$	$+$	$-$	$-^{b}$	$-$	$-$
2005-2012	85	$+^{a}$	$+$	$-$	$-^{b}$	$-$	$-$
2005-2013	90	$+^{a}$	$+$	$-$	$-^{b}$	$-$	$-$
2005-2014	97	$+^{a}$	$+$	$-$	$-^{b}$	$+$	$-$
2005-2015	103	$+^{a}$	$+$	$+$	$-^{b}$	$+$	$-$
2005-2016	106	$+^{a}$	$+^{a}$	$+$	$-^{b}$	$+$	$-$
2006-2017	116	$+^{a}$	$+^{a}$	$+$	$-^{b}$	$+$	$-$
Start year 2006							
2006-2012	69	$+^{a}$	$+$	$+$	$-^{a}$	$+$	$-$
2006-2013	74	$+^{a}$	$+$	$+$	$-^{a}$	$+$	$-$
2006-2014	81	$+^{a}$	$-$	$+$	$-^{a}$	$+$	$-$
2006-2015	87	$+^{a}$	$-$	$+$	$-^{a}$	$+^{c}$	$-$
2006-2016	90	$+^{a}$	$+^{a}$	$+$	$-^{a}$	$+^{c}$	$-$
2006-2017	100	$+^{a}$	$+^{a}$	$+$	$-^{a}$	$+$	$-$
2006-2018	104	$+^{a}$	$+^{a}$	$+$	$-^{a}$	$+$	$-$
Start year 2007							
2007-2012	57	$+^{a}$	$+$	$+$	$-^{a}$	$+$	$-$
2007-2013	62	$+^{a}$	$+$	$+$	$-^{a}$	$+$	$-$
2007-2014	69	$+^{a}$	$+$	$+$	$-^{a}$	$+^{b}$	$-$
2007-2015	75	$+^{a}$	$+$	$+$	$-^{a}$	$+^{b}$	$-$
2007-2016	78	$+^{a}$	$+^{a}$	$+$	$-^{b}$	$+^{b}$	$-$
2007-2017	88	$+^{a}$	$+^{a}$	$+$	$-^{b}$	$+$	$-$
2007-2018	92	$+^{a}$	$+^{a}$	$+^{*}$	$-^{b}$	$+$	$-$
Start year 2008							
2008-2015	54	$+^{b}$	$+$	$+$	$-$	$+^{b}$	$-$
2008-2016	57	$+^{c}$	$+^{a}$	$+$	$-$	$+^{b}$	$-$
2008-2017	67	$+^{a}$	$+^{a}$	$+$	$-$	$+$	$-$
2008-2018	71	$+^{a}$	$+^{a}$	$+$	$-$	$+$	$-$
Start year 2009							
2009-2016	52	$+$	$+^{a}$	$+$	$-$	$+^{b}$	$-$
2009-2017	62	$+^{a}$	$+^{a}$	$+$	$-$	$+$	$-$
2009-2018	66	$+^{a}$	$+^{a}$	$+$	$-$	$+$	$-$
Start year 2010							
2010-2018	60	$+^{a}$	$+^{a}$	$+$	$-$	$+$	$+$

Note: $+$ expresses a positive coefficient, $-$ expresses a negative coefficient.
^{a} denotes significance at the 1% level.
^{b} denotes significance at the 5% level.
^{c} denotes significance at the 10% level.
* denotes a p-value very close to being statistically significant at the 10% level.

shorter time windows, which is different from the results of our main model regression over the total time period. Our examination of time windows shows that $DEBT$ is statistically significant in the windows from approximately 2006 until 2016, suggesting that investors were concerned with other financial features of targets in the years both ahead and after this period. The sign of the variable coefficient is negative for windows including 2005 until 2013, while the remaining regressions show a positive coefficient. The regressions including a statistically significant $DEBT$ variable, show all positive coefficients.

The NPM and LIQ variables are not statistically significant in either of the time windows that have been tested. In the window from 2007 to 2018, the NPM is, however, very close to being statistically significant at the 10% level with a p-value of 0.105. The coefficient of the LIQ is negative in all time windows, except one. NPM has a positive sign in most of the time windows, except the ones including 2005 until 2014.

As discussed in section 4.1, the possible inherent duality of certain financial ratios may influence both the coefficient direction and the significance of the proxies included in this study. We have pointed to the possibility that there are opposing effects related to the interpretation of development directions in our proxies, and that industry effects may cause the observed temporal differences. Thus, the differing signs observed for $SIZE$, NPM, $DEBT$ and LIQ, might be due to industry effects that influence how the development directions are perceived and can be evidence for the inherent duality. It is important to note, however, that the proxies with both positive and negative coefficients across the 31 time windows show only statistical significance for either positive or negative coefficients, and never both.

In addition, we include other measures expressing the essential theories in order to reveal whether other measures of the same financial categories in the main model could have some explanatory power over time. If we apply another measure of debt, measured as the debt-to-capital ratio, we find that it is statistically significant in most of the time windows from approximately 2008 to 2018. This is an important finding because it tells us that investors may be concerned with the same variables, but that different functional forms of the variable proxies have implications for how the measures are assessed. In terms of the debt proxy, the debt-to-equity and debt-to-capital ratios measure the same phenomenon but are specified differently in terms of functional form.

We also investigate whether a relative size measure is a better measure of size, based on the belief that whether a target is perceived as big or small will depend on the size of the acquirer. Furthermore, we suspect this measure to better capture relative changes in value, and to support the hypothesis that firms buying firms close to their own size might find realization of synergies more challenging than the firms who are substantially bigger than their targets. We fail to find clear support for this assumption, as neither of the other variables we include shows noteworthy relations to bidder announcement returns.

In conclusion, our findings suggest that different proxies have varying explanatory power over time. The results from the moving window regressions also provide further evidence that accounting ratios expressing dynamics, have substantial explanatory power. One potential challenge that arises when applying a moving window approach to a sample of 120 observations, is that it results in a low number of observations in each regression. These regressions have thus lower statistical certainty, compared to statistical tests conducted with larger sample size. We do however believe that these tests provide us with important information, in that as a minimum, we can conclude that the investors are concerned with different aspects of targets as time passes, which also further confirms the importance and explanatory power of trend measures.

4.4 Industry effects

We have proposed that different industries might have different perceptions concerning the development of the included accounting-based measures. To investigate whether certain industries have similar perceptions, we suggest an industry correction. This may reveal whether our failure to show an effect on the market return is due to the fact that opposing effects lead to a non-significant average, despite them being present.

As reviewed in chapter 3, our data set consists of firms from a wide range of industries. The fact that there were few observations representing the different industry categories, complicate our ability to conduct a proper analysis and to correct for this. As a solution, we merge target categories where we are able to get a more adequate number of observations without merging too many. We assume that merging as few as possible ensures sufficient similarities to detect possible industry effects. Additionally, since many of the industry categories consists of only one observation, merging them in a logical manner is difficult, and would not necessarily provide us with clear results.

The merged category of the "IT Consulting & Services" and the "Professional Services" categories gives us 28 observations, and the regression results are presented in table 10. We find three statistically significant variables, including the intercept. The regression reports that $SIZE$ and LIQ are significant at the 1% level. This is an interesting finding, in light of the LIQ variable having not been significant in any of the previous regressions in this study. Thus, it provides evidence of the discussed industry effects as well as the variable duality, because the LIQ variable has an effect for this specific industry, despite it not being significant in regressions including all industries. In addition, this finding supports the suggestion of Harford (1999), that what is considered as normal cash levels is dependent on the industry. We observe that the coefficient sign of the AT variable, which has been negative for all previous regressions, is positive. The $DEBT$ variable is negative, as opposed to the results of the main regression over the complete time span, as shown in table 5. These results might be additional evidence for the duality of these measures, but the relationships are, however, not statistically significant.

Table 10: Regression analysis of the merged industry category of "IT Consulting & Services" and "Professional Services"

Variable	Coefficients	Standard error	p-values
Intercept	0.011	0.006	0.064[b]
SIZE	0.020	0.005	0.000[a]
NPM	0.001	0.005	0.923
AT	0.005	0.012	0.695
DEBT	-0.005	0.006	0.442
LIQ	-0.014	0.004	0.004[a]
N	28		
R-squared	0.546		
Standard error	0.026		
F-statistics	3.548[a]		

[a] denotes significance at 1% level.
[b] denotes significance at 5% level.

As mentioned, these results must also be viewed critically, because of the low number of observations, which have implications for their validity. We do not find noteworthy results in other merged categories, but our findings indicate that correcting for industry is necessary in order to model the nuances of the variables' impact on bidder announcement return.

We further examine potential patterns in which industries are most frequent over the total time span, with the intention to explain the observed time dependency of the variables. We study this both for each year, as well as for the same time windows that we applied in our moving window approach. The analysis shows that the most frequent takeover industries change somewhat over time, and can thus contribute as a further explanation for some of the result variation observed in the moving window approach.

4.5 Comparison of models excluding potential irrelevant variables

Although we find some evidence of the explanatory power of LIQ if we correct for industry, the variable is neither statistically significant in the main regression model, nor in the shorter time windows. We observe similar results of no statistical significance for NPM. In order to evaluate if our main model improves when removing one or both of these variables, we run regressions on the possible models with and without them, as shown in table 11. Excluding NPM and LIQ variables do not affect the initial coefficient values much, except for the $DEBT$ variable, where small changes in the coefficient are observed if NPM is excluded, as shown in Model (2) and Model (3). The models excluding NPM lead to substantially higher p-values for $DEBT$. This may be due to the correlation detected between them, as reported in table 6. The LIQ variable does not appear to disturb the model to a great extent when it is included, even though a slight reduction in the p-value of the $DEBT$ variable is observed when it is excluded.

Table 11: Comparison of models including or excluding NPM and LIQ variables

Variables	Model (1)	Model (2)	Model (3)	Model (4)
Intercept	0.018 [0.000^a]	0.017 [0.001^a]	0.017 [0.001^a]	0.018 [0.000^a]
SIZE	0.007 [0.000^a]	0.007 [0.000^a]	0.007 [0.000^a]	0.007 [0.000^a]
NPM	0.007 [0.233]	–	–	0.007 [0.213]
AT	-0.021 [0.014^b]	-0.021 [0.015^a]	-0.021 [0.016^a]	-0.022 [0.013^b]
DEBT	0.003 [0.389]	0.000 [0.922]	0.001 [0.805]	0.003 [0.452]
LIQ	–	-0.003 [0.408]	–	-0.003 [0.364]
N	120	120	120	120
F-statistics	6.190^a	5.966^a	7.745^a	5.111^a
R-squared	0.177	0.172	0.167	0.183

Note: p-values are reported in square brackets next to the coefficient value.
^{a} denotes significance at the 1% level.
^{b} denotes significance at the 5% level.

The highest F-statistic is observed in the model excluding both variables, followed by the model only excluding LIQ (Model (1)). All the models excluding these variables do, nonetheless, have a higher F-statistics than our main model (Model (4)), and this test is significant at the 1% significance level in all models.

Model (4) including all the variables, have the highest R^2, explaining 18.3% of the sample variation, whereas the model excluding NPM and LIQ have the lowest R^2 value of 16.7%. To investigate whether the explanatory power of the main model is significantly different from the models excluding variables, we run a significance test of the R^2 and find that this is not true. Thus, we are not sufficiently compensated for the additional variables included in Model (4) compared to the other models in the table. In conclusion, we do not find strong evidence that our main model is substantially better specified than the regressions excluding NPM and LIQ. However, given the confirmations from the robustness test and our findings from the moving window approach, we decide to keep our main model.

4.6 Replacement and inclusion of variables measured as absolute values

In addition to being interested in the development of targets' accounting characteristics, we also consider it to be likely that shareholders are concerned with the basis of the development. For example, if the debt is already is high, and the firm experiences an increase, it is safe to assume that the level of the financial ratio will also be of interest. In order to explore the explanatory power of absolute measures, we include them in our main model and additionally replace the trend variables with their respective absolute values. The absolute values are calculated as the average over the last three immediate fiscal years prior to the announcement, and table 12 reports the regression results. In both regressions, we keep the $SIZE$ variable which already expresses an absolute level.

Table 12: Regression analysis where variables of absolute values replace trend variables

Variable	Coefficients	Standard error	p-values
Intercept	0.015	0.013	0.245
AB SIZE	0.007	0.002	0.000[a]
AB NPM	0.000	0.001	0.968
AB AT	0.003	0.004	0.441
AB DEBT	-0.001	0.001	0.498
AB LIQ	-0.001	0.003	0.729
N	120		
R-squared	0.135		
Standard error	0.053		
F-statistics	3.548[a]		

[a] denotes significance at 1% level.
[b] denotes significance at 5% level.

Table 13: Regression including absolute values in the main model

Variable	Coefficients	Standard error	p-values
Intercept	0.018	0.014	0.190
AB SIZE	0.007	0.002	0.000[a]
AB NPM	0.001	0.001	0.637
AB AT	0.002	0.004	0.720
AB DEBT	-0.001	0.001	0.384
AB LIQ	0.000	0.004	0.991
NPM	0.004	0.007	0.519
AT	-0.021	0.009	0.023[b]
DEBT	0.006	0.005	0.250
LIQ	-0.003	0.004	0.464
N	120		
R-squared	0.192		
Standard error	0.052		
F-statistics	2.895[a]		

[a] denotes significance at 1% level.
[b] denotes significance at 5% level.

The regressions show that both the inclusion and replacement of the absolute values do, in fact, weaken the main model to a great extent. Tables 12 and 13 show that all of the included variables expressing absolute levels show high p-values, hence none of them seem to have a statistically significant impact on the announcement return to acquiring firm. In

addition, table 12 show a R^2 of 13.5% for the model where the trend variables are replaced, compared to the main model with 18.3% as reported in table 5. For the regression shown in table 13, which includes the absolute values in the main model, we observe an increased R^2 to 19.2%. As with the model comparison in table 11, we run a significance test of R^2 to test whether the explanatory power of the main model is significantly different from the model including absolute values. We achieve a p-value of 0.887 and thus fail to detect a statistically significant difference.

These findings may indicate that the direction of development of target financial situation seems to be more important than the absolute levels of financial ratios. We propose that one explanation for these results could be that a fraction of the target firms in the sample are founded recently, and that acquirer shareholders are, therefore, more concerned with future levels rather than current levels. Thus, we suggest that a measure expressing change will reveal more about target potential than a measure expressing an absolute level. Based on this conclusion, we question whether the regressions, showing no statistically significant relations, might be a confirmation as to why we do not find studies.

5 Conclusion

In this study, we investigate whether trends in accounting measures can help explain the acquiring firm's stock return at the announcement of M&As. We find several interesting aspects.

First, we find that target absolute size and trends in asset turnover have explanatory power on bidder announcement returns. Our control variable, absolute $SIZE$, is statistically significant with a positive impact on the announcement return. This finding supports the result of Fuller et al. (2002), who document that bidders experience positive abnormal returns when acquiring private targets. Further, we show that decreasing AT has a positive impact on bidder announcement returns, which is in line with the inefficient management hypothesis. None of the three remaining trend variables, $DEBT$, NPM, and LIQ, are statistically significant in the main model. We explore whether these results are due to opposing effects that result in an average with no statistical significance.

Second, with a moving window approach, we find that the impact of trend variables is time-dependent. We observe that trends in debt-to-equity are statistically significant in parts of the time span, as well as we document that the coefficient signs of the explanatory variables differ in the different time windows. We hypothesize that some of the observed time dependency might be due to industry effects because takeovers might be more frequent in certain industries in certain time periods. Correcting for industries provides us with some evidence that different industries are concerned with particular features.

Third, we test whether the main model is better fitted when excluding potentially irrelevant variables. Our results indicate that by excluding LIQ and NPM, we achieve a better suited model.

Finally, we both replace and include absolute values of our chosen variables in the model, but none of these are statistically significant. This leads us to believe that the development of financial measures is more important to shareholders when evaluating M&A potential than their respective absolute values. We assume that this may be due to the number of target firms in the sample that is recently founded, in which shareholders are more interested in the potential development, rather than the current levels. Perhaps, more interestingly, we also wonder if the regression results of the absolute values confirm why we cannot seem to find any similar studies conducted in the past.

When evaluating the results of this study, we need to be aware of its possible limitations. In order to achieve robust regressions, a relatively large sample is required. However, what number of observations defined as an "acceptable sample size" is unclear. If we do not obtain a sufficient number of observations, it can result in large deviations from the sample data and the population. Hence, we must be critical to the sample size of 120 observations, and more data would be preferable and potentially provide more reliable results. We encourage future studies on this topic to include greater markets, such as bigger regions or global markets. This will solve the issues arising from a limited sample and contribute to more robust results. Including more observations will allow future studies to investigate industry effects and the duality we suspect to characterize the trend measures more carefully. Furthermore, a greater sample might create a more reliable result when investigating industry effects because it will grant each industry with more observations.

As discussed in section 2.1, the restrictions of the market adjusted return model might lead to bias in our model. In order to increase the robustness, future studies should apply different models to calculate abnormal returns including the market model or other models that estimate betas. Furthermore, we suggest the inclusion of both short- and long-term

windows to evaluate the announcement returns. The findings of Oler et al. (2008) indicate that when an event is infrequent or complex, longer-term measures should also be included. Besides, if the market reaction to an announcement is not efficient, then our short-term window cannot capture the real effect, and only measuring the returns in the short-run is a possible shortcoming of this study.

Also, the use of a cross-sectional approach to model market events that have occurred in different time periods do not allow us to control properly for time. In this study, we use a moving windows approach to explore time differences, but we suggest the appliance of more complex approaches to model time in future research, such as a panel data.

There may also be a potential weakness related to the potential lack of important financial measures. There are many financial aspects involved in explaining the market reaction to an announcement, and we cannot be sure that we include all relevant measures in this study. In other words, there may be important ratios missing from our model that may affect the reliability of our chosen model. Additionally, accounting-based measures can only explain a fraction of the market reaction to a M&A announcement.

In conclusion, we suggest modeling trends in ratios as an approach for further research. Our results indicate an alignment of management's and shareholders' preferences regarding target features, and we document that trend measures contribute with other information than absolute measures. We, therefore, recommend studies that apply accounting-based ratios, such as the target prediction literature, to assess trend measures.

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