



CHALMERS

Evaluation of Financial Forecasts

An empirical study of revenue forecast accuracy and bias within M&A

*Master of Science Thesis
in the Management and Economics of Innovation Programme*

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Dennis Persson



Lars Lind

Abstract

Prior research has found evidence of management forecast bias and accuracy to significantly differ across a number of determinants. However, little research has been carried out during non-normal operations such as mergers and acquisitions (M&A). It can be argued that this context can induce further financial incentives on managers resulting in overly optimistic forecasting behavior. The purpose of this master thesis was to investigate revenue forecast issued by the target firm undertaking M&A activity. In conjunction to previous research, this thesis analyzed forecasts with respect to (1) firm size, (2) financial condition, (3) industry and (4) business cycle. The findings were based on a cross-sectional study with primary data from 103 revenue forecasts issued by the target firms during the years 2005-2011.

The results showed that the revenue forecasts were generally optimistic with an average bias of 17 percent over a three-year period. In addition, smaller firms and firms with higher variation in historical revenues exhibited a significantly higher degree of optimistic bias and lower accuracy. No statistical significance was found between forecast accuracy and bias across the selected industries. A positive significance was found in bias between macro-economic (GDP) forecasts and managerial forecasts, implying that similar overestimations and underestimations were prevalent during the business cycle. In contrast to earlier research findings, financial condition was not shown to explain forecast performance with any significance.

Conclusively, the findings in this study contributes to research with new evidence regarding managerial forecasting behavior in M&A and provides insights that may support practitioners within M&A transactions to better understand the implications of revenue forecasting in this context.

Keywords: *Management forecast, revenue forecasting, forecast performance, forecast accuracy, forecast bias, incentives, mergers and acquisitions*

Acronyms

Acquirer/buyer - the buying party in M&A.

Cognitive bias - a type of error in thinking that occurs when people are processing and interpreting information.

Due diligence (DD) - an in depth review of a potential investment regarding financial, legal, commercial activities etc.

Expectation – the change between two consecutive time periods in the forecasts i.e. expected change

Financial forecasting - prediction of future financial conditions for a firm, organization or country.

Forecast error - the deviation between a forecasted value and corresponding outcome.

Forecast variance - the dispersion of forecast errors.

Forecast bias - a measure indicating when forecasts are consistently too high (optimistic) or too low (pessimistic).

Forecast accuracy - a combined measure of forecast variance and forecast bias.

Information memorandum – a document provided by the target firm with non- public information, including forecasts, customers, operations, business strategies etc.

Mergers and acquisitions (M&A) - combination of two or more businesses forming one single entity as a result of a transaction or when a company is purchasing shares and becomes the owner of another firm.

Target firm - the firm/s being subject to sale in M&A.

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1. Introduction

This thesis investigates revenue forecast issued by the target firm in a merger and acquisition (M&A). The focus is on evaluating the managerial forecasts, their expectation, and in particular the bias and accuracy along a set of determinants based on a sample of potential M&A transactions. The forecast itself yields insight into the manager expectation but the value of a forecast depends on its performance which is related to the *forecast errors* i.e. the discrepancy between the forecast and the outcome. The *forecast accuracy* consists of its two components - *forecast variance*, measuring the dispersion of errors and *bias*, measuring the direction of errors (Diebold, 2006). In practice, a *forecast bias* is when a forecast are consistently too high (optimistic) or too low (pessimistic) (Blackstone, 2013).

An organization typically relies on forecasts to cope with future business developments and scholars have found that the process of producing forecasts generate forecast bias (Lovell, 1986; Keane and Runkle, 1998), which negatively influences its accuracy. In particular, one less researched area is revenue forecasting (Mutlu, 2013). Revenues are both among the most difficult thing to forecast (McIntyre, 2002), and among the most critical (Koller, Goedhart & Wessels, 2010). Furthermore, this is an area where forecasters tend to be overly optimistic (Fildes, 2014).

A part of a business valuation is to evaluate the target firm's forecasts from a standalone-basis through discounted cash-flow methods. Indirect effects of a less accurate forecast are the inability to understand market dynamics, customer behavior and uncertainty of future event etc. (Danese & Kalchschmidt 2011). A less accurate forecast therefore reduces the buyer's objectivity and may lead to a non-representative valuation and consequently incorrect price negotiation during M&A. Inaccurate forecasts also have implications on investors, analysts and additional stakeholders with interest in M&A. For instance, investors and analysts can react to a significant mismatch between outlook guidance and actual results, which can make the share price suffer (KPMG, 2007). Adjusting for bias exhibited in prior forecasts has been found effective to generate more accurate projections by removing known bias (Shaffer, 2003).

The forecast accuracy is generally a result of the objectivity of the analyzed environment, the process of generating input variables and the method by which the forecast is produced (Bathcelor & Dua, 1990). It has been found to differ along different variables, for instance in small vs. large firms, in financially distressed firms, across different industries and over different time periods (Buettner & Kauder, 2010; Ferris, Jayaraman & Sabherwal 2013; Bretschneider et al, 1997). Interestingly, Stunda (1996; 2000) found differences in managerial forecasts during normal and non-normal operations (in particular during M&A) pointing to different incentive structures as the underlying cause. In fact, incentive structures are believed to be a prime cause of forecast bias (Cheng, Luo & Yue, 2013; Sun & Xu, 2012). The other main stream of research emphasized cognitive biases i.e. patterns of deviation in judgment (Haselton, Nettle & Andrews, 2005). Cognitive biases, in the generation of forecasts, tend to limit the objectivity and result in lack of utilization of effort (Segall, 2010).

In short, understanding the implications of the M&A context on forecasts on the basis of the internal factors of a firm, its financial condition and size, as well as external factors across industries and the business cycle would shed some new light on managerial forecast behavior in this field of research. For practitioners involved in M&A transactions, this report could also provide insight into the significance of financial forecasts in business valuation procedures.

Purpose and research question

The purpose is to explain forecast expectation, accuracy and bias in M&A with respect to four determinants. Thus, the research question is formulated as follows:

How can expectation and performance of revenue forecast issued in M&A be explained with regard to (1) firm size, (2), financial condition, (3) industry and (4) business cycle?

This thesis will empirically investigate 103 revenue forecasts from a set of potential M&A in Sweden within the period 2005 - 2011 and analyze them with regard to internal and external determinants expressed above.

Delimitations

This thesis is delimited in multiple ways. Firstly, all forecasts are issued in the context of M&A. As such, it targets a rather narrow context of forecasts where specific incentives arise, and therefore distinguishes itself from the more widespread research in general managerial

forecasts or external analysts' forecasts. Secondly, it specifically addresses revenue forecasts although it recognizes and draws upon much relevant research carried out in nearby academic fields, such as earnings forecasts. Thirdly, the thesis primarily aims to quantitatively assess discrepancies between forecasts and realized outcomes and consequently disregards the forecast process. Additionally complementary financial information for each transaction was collected to analyze forecast performance in connection to four specific determinants. However, with limited information on inputs used for the forecasts, the possibility to qualitatively assess how or why a forecast was carried out is severely limited; in other words, analyzing the inputs to a forecast. Instead, the focus is on the output. As a result, it may not be possible to explicitly assign the cause of the identified accuracy and bias. Fourthly, the analyzed forecasts were issued between the years 2005-2011 in primarily the Swedish market. This of course limits the generalizability in time and space.

Disposition

This thesis is structured as follows: Initially, the literature review and hypothesis development introduces the reader to the concept of revenue forecasting through its usage in business applications and in M&As. Afterwards, it recaps existing theory in the four determinants and results in hypotheses for each one. This provides a clear guideline for how the analysis should be conducted. The methodology section then describes the research strategy, design, method, sampling issues and a variety of concepts to help understand the quality of this thesis.

The empirical section introduces the findings which includes the final sample of 103 potential transactions and the determinants - industry, firm size, financial condition and business cycle. Following is the analysis section where the results of statistical tests are discussed to provide deeper insight into the data and to confirm or reject the hypotheses. Additionally, the findings are analyzed with respect to the findings in the literature review, where similarities or differences are gauged. Ending this thesis is the conclusions, which highlights key takeaways and suggests further research.

2. Literature review and hypotheses development

A widely held perception among researchers is that optimistic forecasts are induced either by cognitive biases or incentives (Abarbanell & Lehavy, 2003). The latter corresponds to limitations in how humans think and process information, which leads to systematic errors (Ritter, 2003). Incentives play a role when the forecaster willfully introduces bias to serve some other need, and thus produces optimistic or pessimistic forecasts deliberately. When the forecaster is completely rational (thus not exposed to the cognitive biases) and aims solely to optimize accuracy (thus not exposed to any other incentives) and still systematically generate bias, a third and less mentioned explanation may be that the forecaster lacks sufficient data about changes in the target variable (Batchelor, 2007).

Cheng, Luo and Yue (2013) examined how the precision of earning forecasts i.e. specificity, related to managerial incentives. They found confirmations that managers are likely to manage the forecast precision when investors cannot assess the precision of information used to generate the forecast (Cheng, Luo and Yue 2013; Sansing, 1992). Appendix A describes some ways forecasts can be composed and presented with varying precision. Revenue forecasts have consistently been pointed out to be over-optimistic in the literature, even though some researchers have provided contradictory results. Müller (2011) investigated undisclosed revenue forecasts and found them to be significantly pessimistic. A finding of this character is not in line with the general perception of revenue forecasts (Müller, 2011). The intention for this thesis is to contribute to existing research by evaluating revenue forecasts and identify which of some commonly researched determinants are applicable, if any. Although contradictory evidence has been found, this thesis sheds light on forecasts within M&A, which has been relatively unexplored.

Revenue forecasting

Given the scope of the research question, this thesis will focus on revenue forecasts on the firm level. Revenues are rather unexplored compared to the much more frequent literature on earnings (Mutlu, 2013) which is surprising since, for a firm operating in a financial market

relying on profit for survival, revenue forecasting may provide insight with regard to customers, budgeting, product sales and more. Revenues is also more “pure” compared to earnings, in the sense that earnings are more frequently subject to creative accounting techniques and possible misleading’s (Müller, 2011). Such measures can compromise the validity of the data when comparing figures across companies and over years, which is why there are several measures to undertake when analyzing financial statements, see Appendix B for more information about this topic.

Out of all the financial items to forecast, revenue is also sometimes considered to be the most difficult one (McIntyre, 2002; Tennent & Friend, 2005). This is unfortunate given that it is critical to valuation and strategy assessment (Koller, Goedhart & Wessels, 2010). A reason for this is the large number of uncertainties involved. Unlike internal cost factors, the external macro economy has a significant impact on revenues and is largely beyond the control of an individual firm. The importance of understanding revenues are further motivated by realizing that costs and profits are typically conditioned on its outcome. In fact, Koller, Goedhart, and Wessels (2010) argue that the value of a company is ultimately determined by the revenue growth and return on invested capital, and further goes on to say that revenue growth sometimes drives return on invested capital on its own. Thus, the argument is made that estimating revenues is not only the most difficult factor; it is also the most important. For these reasons, one might expect companies to devote most time and effort on this variable, which is also what several authors advocates, especially in cases where revenues are expected to grow quickly (Koller, Goedhart & Wessels 2010; Wellings, 1998).

Completely assessing the performance of forecasts would require an adequate consideration of the forecasting process and methods. Uncertainties that are beyond firms control may make it difficult to control for the desired accuracy but not the forecasting process used, and the resources committed (Gilliland, 2010). Forecasters can apply a variety of methods ranging from pure quantitative econometrical models to a more judgmental “gut feeling” approach, each with its use depending on the importance and nature of the forecasted variable. When it comes to forecasting revenues, a general recommendation is to break down the figures in individual markets, customers and by prices or products (Tennent & Friend, 2005). Appendix A describes forecasting processes and various methods in more detail.

Forecasts in M&A

Some firms release their forecasts to the public eye in quarterly, semiannual or annual reports. The purpose of these financial forecasts is multifold. On a general level, they serve to inform stakeholders of the future expectations of performance. Additionally, the forecast may aim to satisfy shareholders' need for information to lend credibility, to limit freedom in earnings management (Wasley & Wu, 2006) or to control market price reactions (Baginski, Hassel & Kimbrough, 2004). Forecasts also have special purposes in the case of an M&A - The seller informing the buyer about its business to facilitate a reasonable valuation and in the longer run to support a beneficial transaction (Schill, Chaplinsky & Doherty, 2000).

Within M&A, forecasts are generally not published. Due to the sensitivity of the deal they are confidential and part of an information memorandum. There are reasons to suspect that the incentives in these situations are unique. Müller (2011) analyzed undisclosed revenue forecasts and assessed the extent of strategic deception and cognitive bias in these forecasts. Contradictory to mainstream research findings, he found undisclosed forecasts to be significantly pessimistic. Thus, it can be argued that under circumstances when managers' forecasts are not being subject to market recognition, managers have fewer incentives to produce optimistic forecasts.

Stunda (1996; 2000) researched whether there were any differences in the seller's disclosures of earnings in normal operations and non-normal operations (M&A in particular) and found indications of more positive forecast bias in the latter. A plausible explanation is the substantial premiums that the target receives in conjunction with the transaction. This is a prime example of a unique incitement directly influencing the forecast bias. See Appendix C for more descriptions about M&A and the context in which these forecasts are issued.

However, directly observing and quantifying these types of incentives are problematic since they are embedded within processes, methods and structures in the firm. The same argument applies to cognitive biases, which are in essence embedded in individuals. Consequently, most research, including this, will thus not directly measure to what degree incentives and cognitive biases exist but statistically assess differences given a variety of determinants and to the extent possible make suppositions of their cause. Hence, it can be noted that there are two ways to go about evaluating forecasts, by their input and by their output. Analyzing the input would correspond to assumptions and data input while analyzing the output involves either replicating the forecast approach to enable comparisons across different sets of data or

directly assess the output. It is the latter approach that this report revolves around, by comparing outcomes and using measures of bias and accuracy to gauge the forecast performance. More on forecast evaluation procedures can be found in Appendix D.

To conclude, revenue forecasts are important and lack sufficient coverage in current literature. Factors influencing the accuracy and bias can in large be categorized as cognitive biases and incentives. Differences in performance can be understood by comparing along different determinants. These determinants belong to either internal factors related to the firm or external factors relating to the environment at large. The choices of determinants in this thesis are based on earlier research carried out on management forecast performance. It is worth mentioning that much research has been conducted on earnings forecasts and forecasts issued by analysts'. Stunda (1996; 2000) is, to the authors' knowledge, the only scholar who has investigated management forecasts in M&A. However, he did not address any determinants in his research. Hence, this thesis contributes by concentrating on the above-mentioned determinants, focusing on revenues and managers as forecasters in private M&A.

(1) Firm size

Empirical evidence has found forecast bias to vary across firms. Hartnett (2006) managed to develop a relationship between the direction of forecast bias and firm size - large firms tended to underestimate their forecasts more often compared to their smaller counterparts. The authors cited that larger firms relied on their reputation and thus had more to lose when expectations were not met. On the same note, smaller firms had more freedom in adjusting reported results and thus easier manage expectations, thus incentivizing them to underestimate forecasts as well. Nevertheless, Ota (2006) found that small firms in Japan demonstrated optimism in earnings forecasts.

The objectivity of information available has a direct impact on forecast bias. According to Smith et al. (1996), small firms usually develops their forecast through qualitative rather than quantitative approaches, which tend to have a higher degree of subjectivity. Additionally, Lim (2001) argues that forecast bias is more extensive for smaller firms, being more volatile and experiencing prior negative earnings surprises. Verheul & Carree (2007) found newly started businesses to exhibit higher optimism. Since insufficient information usually constrains small firms to produce a representative forecast under normal circumstances, it is argued that forecasts under non-normal operations will produce more optimism.

It has been argued that larger firms can exercise their expertise through well-developed methods and techniques to generate more accurate forecasts compared to smaller firms. However, a positive relationship has been found between forecast error (bias) and firm size. Larger companies are required to raise extensive amount of capital compared to smaller firms, which limits their ability to issue accurate forecasts (Hsu, Hay, & Weil 2000). Furthermore, large firms are usually more diversified which also affect their forecast accuracy (Hsu, Hay, & Weil 2000). Several researchers have pointed out larger firms to be pessimistic in their forecasts since they are more often subject to scrutiny by public institutions, such as financial analysts (Hsu, Hay & Weil, 2000; Brown, Hillegeist & Lo 2005). Another discussed reason why larger companies issue pessimistic forecasts, is related to litigation risk. This will be discussed further under the industry determinant section.

The preceding discussion suggests that incentives to issue optimistic forecast are mainly prevalent in smaller firms. Existing research thus lacks clear evidence that either smaller or larger firm would exhibit more bias than the other, but findings generally point to larger bias for smaller companies. Consequently, in line with the current research, smaller firms are argued to exhibit larger degree of optimistic forecasts, and are perceived to do the same when being subject to M&A.

H1. Smaller firms will issue more optimistic revenue forecasts and consequently higher optimistic forecast bias when subject to a potential M&A.

(2) Financial condition

The current financial condition of a company can affect management to forecast misleading forecasts. Carcello and Neal (2003) found evidence that firms issued misleading-forecast when their financial condition was unfavorable with intention to attract investors and restore the financial health. The degree of optimism is found to increase as the financial condition is impaired (Koch, 1999). Moreover, under circumstance when the credibility of forecasts are difficult to assess, financially distressed firms are more optimistic compared to healthy firms (Koch, 1999). Ota (2006) found financial distressed firms with high debts ratios and negative results to exhibit more optimism in their earnings forecasts.

Both private and public companies may issue optimistic revenues or earnings forecasts, since these acts as a signal to potential analysts and investors (Müller, 2011). However, issuing non-credible forecast might result in consequences, such as loss of reputation, higher cost of capital and possible legal liabilities, such as lawsuits (Irani, 2003). Koch 1999 analyzed the

relationship between issuing optimistic forecasts and financial distressed firms. He found managers in financially distressed firms to have more incentives and are more ignorant about potential penalties due to the fact that their firm or position may cease to exist. Under such circumstances, security institutions and financial intermediaries are not able to penalize optimistic forecast issued in the past to the same extent (Koch, 1999).

Analyzing the forecast performance issued by firms with poor financial conditions is considered essential with the underlying assumption that these firms will exhibit significantly higher optimistic bias compared to non-distressed firms as argued by prior research. Building on the confirmed occurrence of optimism in financial distressed firms forecasts, the argument is made that these will exhibit more optimistic forecasts compared to healthy firms. Therefore, the following hypothesis will be tested:

H2. Firms in poor financial condition will issue more optimistic forecasts and consequently higher optimistic forecast bias when subject to a potential M&A.

(3) Industry

The industry in which a firm operates may have a direct impact on the degree of forecast accuracy, some industries are inherently more difficult to forecast compared to others. Industries with tangible activities and relatively consistent demands may be surrounded by less uncertainty compared to industries where demand is more volatile and hard to predict (Hsu, Hay & Weil, 2000). Dev and Webb (1972); Goodwin (1989) and Jelic (1998) introduced findings about the variance of forecast accuracy across industries. Dev and Webb (1972) investigated firms in construction industry, grocery industry and timber and road industry. The forecast accuracy was found to vary substantially across these industries. Goodwin (1989) analyzed newly listed companies divided into high technology firms, manufacturing/engineering and services and found that the nature of the industry had significant implication on the forecast accuracy. Although, these evidences were found during the latter part of the 20th century, they are argued to be relevant due to the fact that markets have, if anything, become even more dynamic, global and interconnected and consequently more uncertain. Additionally, product life cycles have been substantially reduced, which also increases the complexity to issue accurate forecasts.

Katz, Zarzeski and Hall (2000) examined analyst forecasts and used three measures of industry characteristics as control variables. Based on measures in earlier strategic literature they used industry dynamism, industry munificence and industry complexity - referring to the

industry growth rate, heterogeneity of firms, and variability in growth. Their findings showed, as expected, that higher degrees in each factor resulted in more forecast errors due to increasing uncertainties.

There is rich evidence that optimistic bias is predicted to be more prevalent for companies surrounded by dynamic and uncertain markets where revenues are hard to predict (Lim 2001; Espahbodi, Dugar & Tehranian 2001; Kanagaretnam, Lobo & Mathieu 2004; Hui, Wei, & You, 2013; Hartnett, 2006). For instance the forecaster might neglect information regarding negative development of an industry, due to the desire to see it prosper. This refers to the concept of confirmation bias, where individuals tend to search and notice information that confirms their beliefs and simultaneously ignores information that is contradicting (Balsyte & Moeller, 2012; Fisher & Statman, 2000). Confirmation bias will most likely prevail when decision-makers initiate analysis with aspiration of a transaction. It is too common for people to misinterpret or reject findings if it does not confirm their forecasts. (Armstrong, 2001)

Factors affecting forecast accuracy across industries are also perceived to be driven by incentives. Firms operating in markets with high risk to encounter litigation issues will have less incentives to produce optimistic forecasts, but when the risk to encounter litigation is relatively low managers tend to produce optimistic forecasts. It is argued that forecasting can reduce the probability of being sued by presenting sufficient information which firms are obligated to disclose (Brown, Hillegeist & Lo 2005).

Additionally, Tirole (1993) and Datta, Iskandar-Datta and Sharma (2011) argue that firms in concentrated industries are more profitable than those in fragmented industries. Consequently, profitable incumbent firms are perceived to have greater incentives to issue pessimistic forecasts to discourage new entrants (Newman & Sansing 1993). On a similar note, Fisman (2001) researched the associations of competition and forecast bias, basing their standpoint of the backward-looking expectations tendency where firms over-extrapolate on historical data. Taking an evolutionary argument they referred to Nelson and Winters (1982) and argues that firms with inefficient routines ought to be outcompeted and extinct over time. However, protected firms, such as monopolies, lacking competitive pressure, might retain these costly biases. Thus, they expect and find that lower degree of foreign competition yields higher forecast biases, resulting from these backward-looking expectations.

One may argue the existence of industry variations should exhibit similar results compared to forecast issued for normal operations. Thus, the argument is made that forecasts made within

M&A will exhibit extensive optimistic forecast bias. Thus, we would expect to see industries that are more dynamic, faster growing, competitive and more heterogeneous to suffer from more optimism. On the contrary, more concentrated industries and more prone to litigation risks are expected to issue less optimistic forecasts. However, the latter risk is not perceived to be essential in this study since, the forecasts are not being disclosed to market and only works as negotiation basis for the transaction. On this basis, the following hypothesis is made:

H3. Firms in volatile, fast growing, less competitive and fragmented industries will issue more optimistic revenue forecasts and consequently higher optimistic forecast bias when subject to a potential M&A.

(4) Business cycle

The final explored determinant relates to the macro level. It can be argued that the economy shifts the perception of market participants over the course a business cycle, and that it may be self-fulfilling, whether there are real changes in fundamentals or not (Eusepi & Preston, 2011). In other words, forecasters may be unwarrantedly optimistic or pessimistic about the future, influencing their forecasting ability. The question thus becomes if these perceptions are driving forecast errors. In fact, some research has been carried out with this in mind.

Eusepi & Preston (2011) found systematic patterns in forecast errors over the business cycle. Market participants under-predicted interest rates when the market was in an economic upturn and vice versa, questioning the rationality of the forecasters. Caunedo et al. (2011) found similar forecast predictabilities when observing forecasts of macro variables from the Federal Reserves Greenbook and discussed the losses corresponding to over-or under-forecasting, questioning the symmetry of the loss function that is sometimes otherwise assumed. Sun (2012) hypothesized and found strong correlations between Gross Domestic Product (GDP), stock market liquidity and analyst forecast earnings errors, signifying a collectively optimism right before an economic downturn and pessimism right before an economic upturn. Accordingly, he argued that these errors are informative about business cycles. Fritsche and Döpke (2005) conducted a similar research in the German market and found a non-linear relation between macroeconomic variables and few but large forecast errors (i.e. outliers), here showing that underestimations were more prevalent in economic upturns and large overestimations during economic downturns.

The common denominator of the above is that none of them considers forecasts by managers. Unfortunately, there is lacking evidence in this domain. However, Hsu, Hay and Weil (2000)

reviewed existing research on forecasts during IPO prospectures in the 1980s and noted that “economic conditions” were significant in three out of four cases from UK, Hong Kong, New Zealand, indicating that this is not a geographically unique result. They carried out their own research in New Zealand during 1987-1994 and found significance in forms of optimistic forecast bias and less accuracy in year 1987 but not the consecutive years, likely owing to the stock exchange crash that occurred on that year. Ota (2006) similarly tested macroeconomic influence on forecast bias from 1979-1999 and likewise found significance in the Japanese market. Finally, Jiang, Habib, and Gong (2013) observed significant relations in economic downturns and forecast frequency and errors, but not to forecast precision.

Based on these previous findings, it seems clear that the economy does indeed influence forecasters. It can be argued that in M&A settings, the same cognitive biases are likely to prevail in the same way they occur for any market participant. In fact, Baker and Nofsinger, (2010) discussed a specific cognitive bias called the anchoring bias, which is a reference point from which adjustments are made. In particular, they mention that the origin of the starting point derives from previous data, such as the economic growth or the current rate of inflation, implying its possible relevance in forecasting. From the incentives point of view, if IPOs were any telling, then it is expected to identify optimism during the turning points of a business cycle.

Hence, in line with the above, we measure the business cycle during the analyzed period 2005-2011 by the Swedish Gross Domestic Product and construct the following hypothesis:

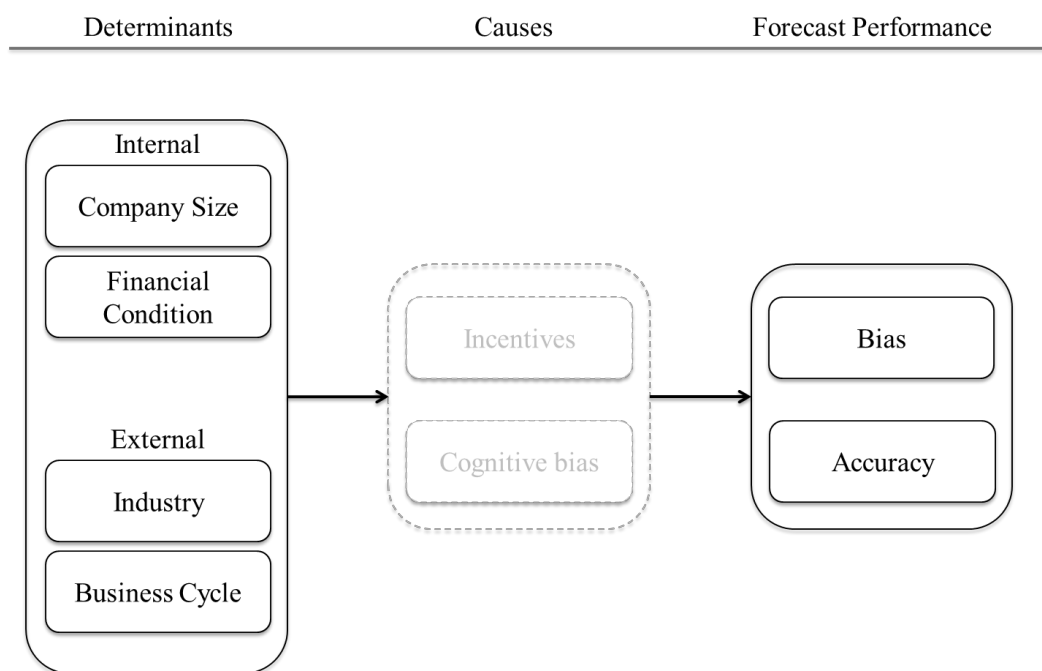
H4. Firms will issue more optimistic revenue forecasts and consequently higher optimistic forecast bias during the peak of the business cycle when subject to a potential M&A.

Framework

An outline of the key concepts can be illustrated in Figure 1. This figure demonstrates the relations between the concepts and presents an overall conceptual framework applied in the forthcoming sections. The figure visualizes the determinants, causes and measures investigated in this study. However, the causes of incentives or cognitive are not measured explicitly in this report but is included for completeness. It should also be pointed out that only analyzing the determinants above is just an introduction to determine the forecast performance in M&A. Additional determinants commonly researched (e.g. business strategies, culture, degree of diversification, prior management forecast errors and forecast

frequency to mention some) would be of interest to obtain a more comprehensive view of the field.

FIGURE 1. Conceptual framework



The selected determinants here represent only a few of many possible. The framework is not comprehensive.

Some authors have focused on the forecast performance of managers during non-normal conditions while others have investigated management forecasts during normal conditions. The differences found in these two contexts entails that non-normal conditions ought to be of interest in academic research. In addition, the focus in previous research has mainly been on earnings forecasts, as this has been perceived to be the most essential to determine the performance of a company. However, contradictory arguments exist whether earnings or revenues are the most difficult to estimate. Even though Table 1 below only addresses a limited number of investigations carried out in the field of forecast performance, it is used to illustrate the degree of bias and accuracy discovered in different but related contexts. An IPO arguably has similar financial incentive structures to M&A since the forecast is issued prior to a major change of ownership. As such, similar forecasting results would be expected between these two settings.

TABLE 1. Prior related research

	<u>Bias</u>	<u>Accuracy</u>	<u>Sample size</u>	<u>Context</u>
Müller (2011)	-6%	20%	6234	Normal but undisclosed, revenues, Germany
Stunda (1996)	21%	N/A	186	M&A, earnings
Stunda (2000)	19%	N/A	419	M&A, earnings
Schatt (2002)	-12%	43%	151	IPO, earnings, France
Firth et al. (2013)	11%	35%	221	IPO, earnings, Australia
Hartnett & Römcke (2000)	2%	18%	114	IPO, revenues, Australia

Miller (2011), Firth et al. (2013), Schatt (2002) and Hartnett & Römcke (2000) measured bias and accuracy using forecast errors = forecast-outcome/|forecast|

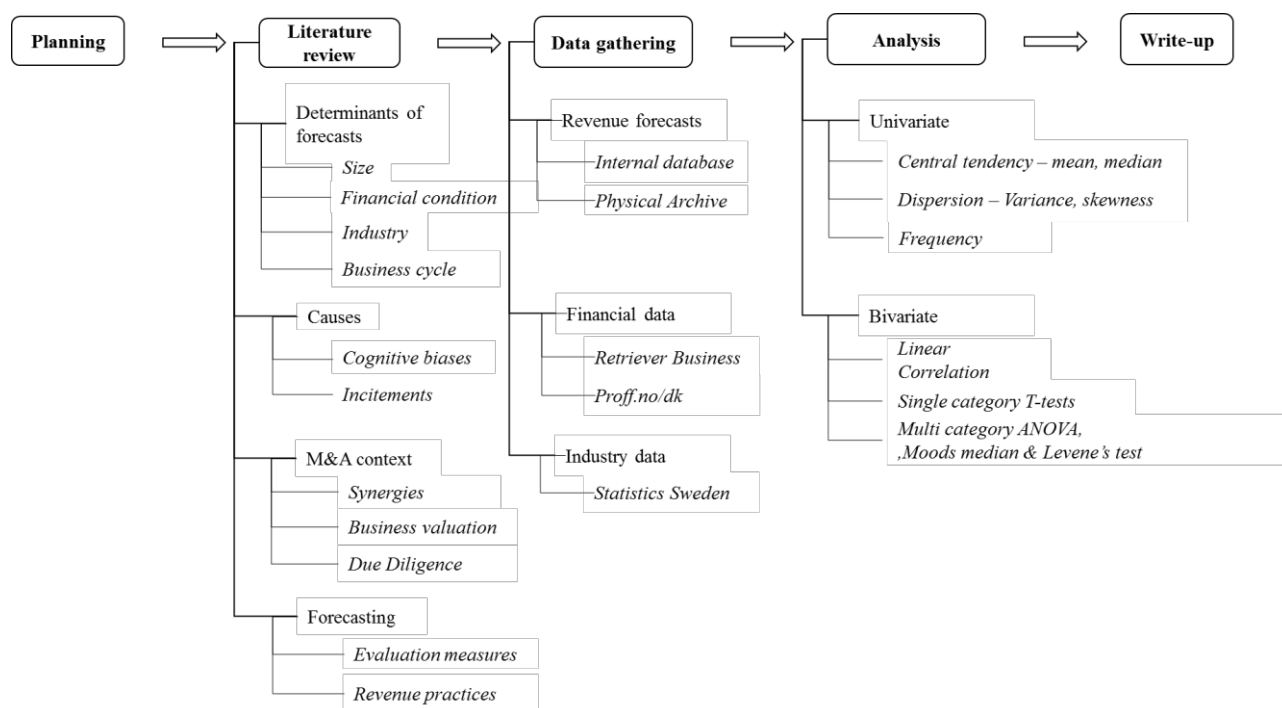
Stunda (1996; 2000) calculates bias and accuracy using forecast errors as forecast-outcome/Share price

3. Methodology

Research strategy

In the present chapter, the reader can appreciate the methodological considerations that went in to this thesis. It was carried out in accordance to a standard master thesis time period of around 20 weeks, starting in early September 2014 and ending in late January 2015. With exceptions of brief visits to Stockholm, it essentially took place in Gothenburg, Sweden. Looking back, the time was largely divided into periods of planning, literature reading, data gathering and processing, analysis and write-up, in that order. See figure 2 for an approximate representation of the thesis work.

FIGURE 2. Research process



This figure represent the research in a linear fashion. However, several parts were overlapping and somewhat iterative in nature.

The research question put several conditions on the choice of research strategy and methodology. While the purpose of explaining forecast expectation, bias and accuracy can be tackled in many ways, here a quantitative approach was used to coincide with the main source of data that was available - financial forecasts. In line with this, a more deductive type of research was selected whereupon existing theory would form the foundation for developing

hypotheses. However, since no general and applicable theoretical framework was found in the domain of managerial forecasting performance, a variety of literature had to be reviewed into a literature review. Using a quantitative research strategy has the benefits of presenting objective and generalizable conclusions as long as the research is properly executed. It may contribute to academia by providing further evidence on when or where certain existing theories carries weight. In particular, whether they had bearing in the specific context of M&A.

The main drawback is the difficulty to properly explain the cause of forecast bias and accuracy given the lack of input from the forecasting process. Seeing how the major causes are believed to derive from incentives and cognitive biases unique to the individual forecaster, a thorough assessment would require qualitative data from specific situations. A qualitative approach with further input from the forecasting process would also benefit to contextualize findings and its implications, and possibly help draw casual inferences of the plausible causes of forecasting performance. To this end, the current method puts limited weight on explaining and predicting, and more so evaluating forecast performance by contrasting the findings over the four analyzed determinants and through statistical analyses.

Research design

Bryman and Bell (2011) discusses various research design choices and categorizes them as either experiment, case study, cross-sectional study, longitudinal study or comparative design. The choice of design should provide guidelines regarding variable associations, generalizability, applicability of the findings in the specific context and temporal appreciation. Following Bryman and Bells (2011) classifications, this thesis most closely follows a cross-sectional study. This design is characterized by a collection of a large body of data at a single point in time to detect associations between at least two variables. Although such a research design typically involves social surveys, here, archival data was used and discussed in the upcoming section.

The implication of a cross-sectional study is the focus on variations by taking a snapshot of a population. Naturally, sampling issues becomes a vital question to consider and is therefore concerned in detail in this report. The prime strength of this research design is its ability to statistically assess a large body of data and generalize the findings. In addition, the opportunity to be specific about the data and data analysis should yield high transparency, which adds to the credibility of the conclusions. No other research designs other than the

cross-sectional design were found to be appropriate to answer the research question, lacking either context relevance (experiments), generalizability (case study) or simply the having the wrong focus (longitudinal and comparative design).

Research methods

Archival data was the foundation for the empirical investigation. The primary sources of information were:

- 1) The internal digital database and physical documents from due diligence engagements of the audit firm KPMG AB.
- 2) Annual reports Retriever business, Proff.no and Proff.dk.
- 3) Industry data from Statistics Sweden (Statistiska Centralbyrån) and GDP data from The Swedish National Institute of Economic Research (Konjunkturinstitutet).

From these sources, quantitative data was collected in forms of financial data, forecasts from Information Memorandum reports or due diligence reports and statistical reports.

The quantitative data was primarily the revenue forecasts but also data from financial statements. One key issue was the reliance of secondary quantitative data since it was impossible to assess its validity. It came very unstructured and suffered from absence of some data points, which ultimately limited the sample size. This required a large degree of data processing in the coding process which may have led to unwillingly coding errors, and caused comparability issues across several forecasts where they differed. On the one hand, there was no reason to assume that forecasts themselves were altered but rather represented the actual forecasts at the time of their creation. On the other hand, certain issues still arose, for example when the forecaster was undefined, when they covered different time periods or when they did not specifically define the forecasted object. From the financial statement, it was sometimes noted that various data points differed significantly between different years, which raised an alarm as to the cause of such changes - whether they were a part of restructuring within a corporation, an M&A or simply a change in accounting principles. These impeded the transparency and had to be taken into consideration to ensure justified data throughout the study. It is the authors' hope that such issues were dealt with appropriately and thus would not play a significant part in the end result.

Sampling process

This section describes the sampling process and addresses similarities and differences between the initial sample and the final sample. The final sample consists of 103 potential transactions and thus it would not be feasible to randomly select a smaller population for the purpose of obtaining an unbiased sample. Such a sample would be too small and pose difficulties in gaining statistical relevance. Since no random sample has been generated, the study uses a representative sample as the second most viable approach. However, this necessity uses an even distribution of transactions to avoid weighty sampling errors. This section describes the distribution of transactions over the analyzed years, industries and geographical origin.

If the population represent the entirety of the M&A activity in Sweden in the years 2005 - 2011 then the accessible population consists of all potential transactions available for analysis, by being subject to a KPMG due diligence engagement. These were essentially stored in digital databases and physical archives in form of documents and binders. Since the physical archive was largely inaccessible, the large bulk of the transactions were found in the database and physical archives were not further explored to support the sample population with additional transactions.

Distribution over years

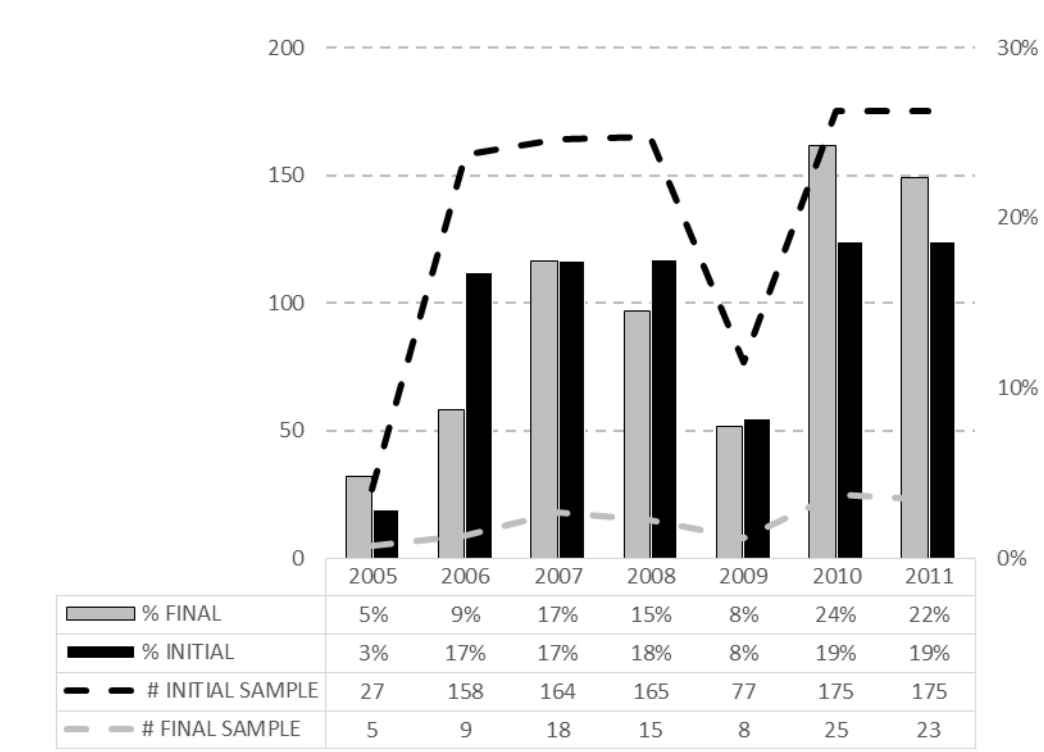
The initial sample consisted of 944 potential transactions distributed over years 2005-2011. The “potential” refers to the fact that the transactions include both those that ended up in an M&A and those that did not. Following the trend line in Figure 3 shows transactions to be fairly distributed over 2006-2008, where the numbers of transactions are rather similar (17-19 percent of the total sample). Additionally, there is a minor increase during 2010-2011 for one or two reasons. First, there may have been a higher interest in M&A after the economic downturn. Secondly, more recent due diligence engagements have been stored and are consequently more accessible.

The number of transactions initiated during 2005 and 2009 stands out compared to the rest of the sample. The database used reflected only the two months of 2005. This explains the small amount of transactions for this year (3 percent of the total sample). The lower number of transactions in 2009 is argued to be due to the contemporary economic downturn, which may have momentarily lowered the interest in M&A activities (8 percent of the total sample). These years are characterized as potential outliers, which may cause non-representative

numbers when further analyzing the data. Extreme values will arguably have higher impacts on average numbers for these years.

When missing data had been taken into consideration, a total number of 103 transactions were acknowledged and represents the final sample. Similar to the initial sample, 2007-2008 represents 15-17 percent of the final sample and 2010-2011 represent 23-25 percent. Looking at year 2005 shows that the final sample consists of 5 percent versus 3 percent of the initial sample. This equals to 5 transactions of the final sample. Moreover, surprisingly the year 2006 stands out as 158 transactions were identified but only 9 transactions were included in the final sample. Lastly, the year 2009 is equally distributed between the initial and final sample, despite that only 8 transactions were included in the final sample.

FIGURE 3 Transactions distributed over years 2005-2011



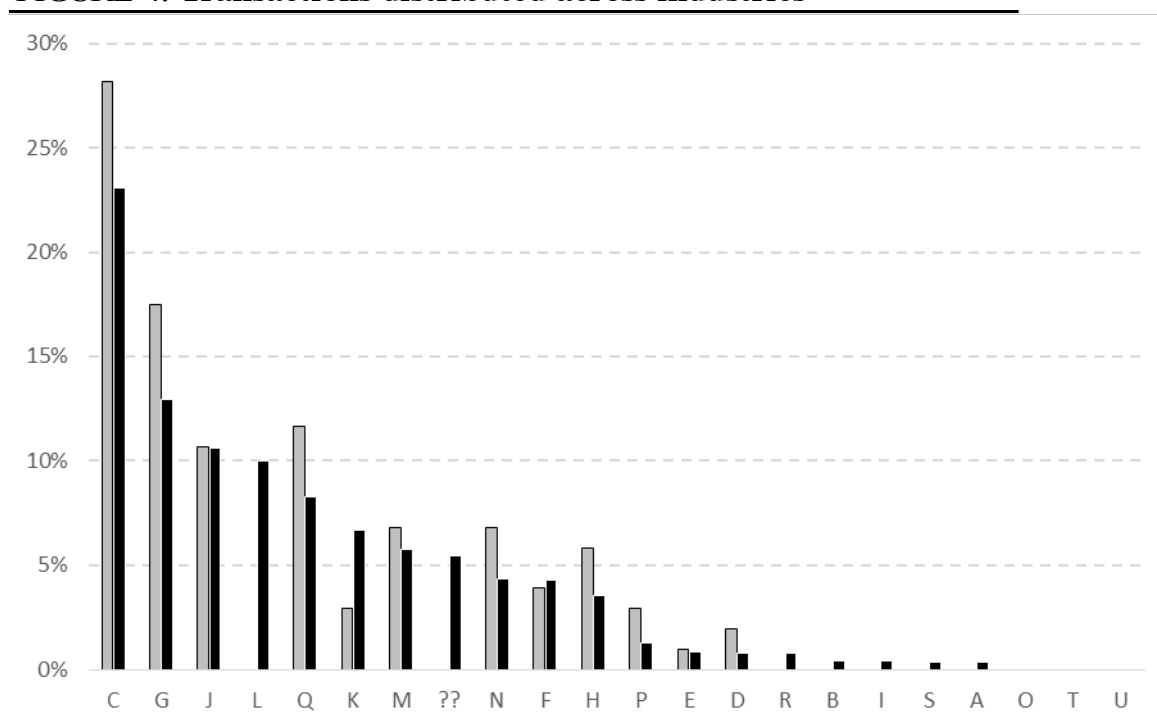
The transactions are fairly evenly distributed with the exception of the year 2006 where many transactions were cut.
The black bar represent the initial sample and the grey bar, the final sample

In conclusion, 2005-2006 and 2009 are potential outliers with regard to transactions distributed over the years. When these years are being analyzed individually, extreme values have to be considered.

Distribution of industries

SNI categorization was applied to categorize firms into different industries (See Appendix E for description of the SNI categories). Figure 4 shows the number of transactions with regard to industry classification. Moreover it exhibits a fairly unequal distribution across industries.

FIGURE 4. Transactions distributed across industries



Industry L, representing real estate activities, were purposely left out.

The black bar represent the initial sample and the grey bar, the final sample

See Appendix E for the complete representation of each character and its corresponding industry

Manufacturing companies “C” dominates both initial and final sample. The second biggest category is *wholesale and retailing* “G” and thirdly “J” represents companies in the *Information and communication industry*. This category is generally heterogenic as it consists of companies from *data consultation* to *publishing activities*. Category “L” is the third biggest category but no transactions were included in the final sample since it refers to *real estate activities*. Forecasts in this “L” category were argued to be very different from the other industries since they are typically based on very predictable rents. For this reason they were been left out.

Another category worth mentioning is “Q” where *Human health and Social work activities* can be found. Following significant deregulations within industries in the “Q” sector may have resulted in a new interests in M&A and explain the large representation within this

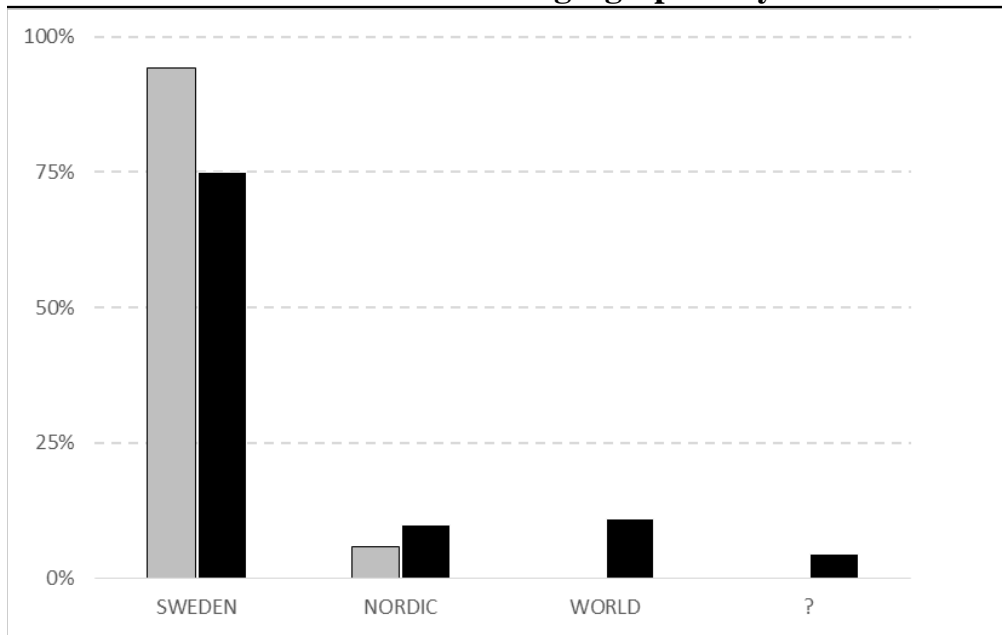
sample. Companies marked with “??” are those for which an industry could not be determined.

In large, the final sample reflects the initial sample well. As Figure 4 shows, the percentage of companies in the final sample is greater compared to the same industries in the initial sample and can be explained from the exclusion of L. The larger categories (excluding “L”) are of appropriate size for statistical analysis but many smaller categories are not.

Distribution of geographic location

It was our initial desire to analyze a diversified pool of transactions issued in many different countries, not only to increase the amount of transaction analyzed but also to analyze specific characteristics for individual countries. However, as Figure 5 below presents, Swedish transactions dominates both the initial and the final sample and counted for 75 percent of the initial sample, which equals up to 708 transactions. The remaining 236 were divided into three categories, Nordic (94 transactions), World (103 transactions), and finally “?” referring to those with unidentifiable origin. A Nordic transaction refers to a forecast issued by a company in Norway, Denmark or Finland. Transactions marked with World represent the remaining countries. The reason for the increased number of Swedish transactions in the final sample is explained by the limited access of information, most notably annual reports for non-Swedish firms. Many of the foreign companies included in the initial sample are companies for which annual reports were inaccessible. However, a handful of transactions in the final sample could be obtained which represents 6 percent in the Nordic category.

FIGURE 5. Transactions distributed geographically



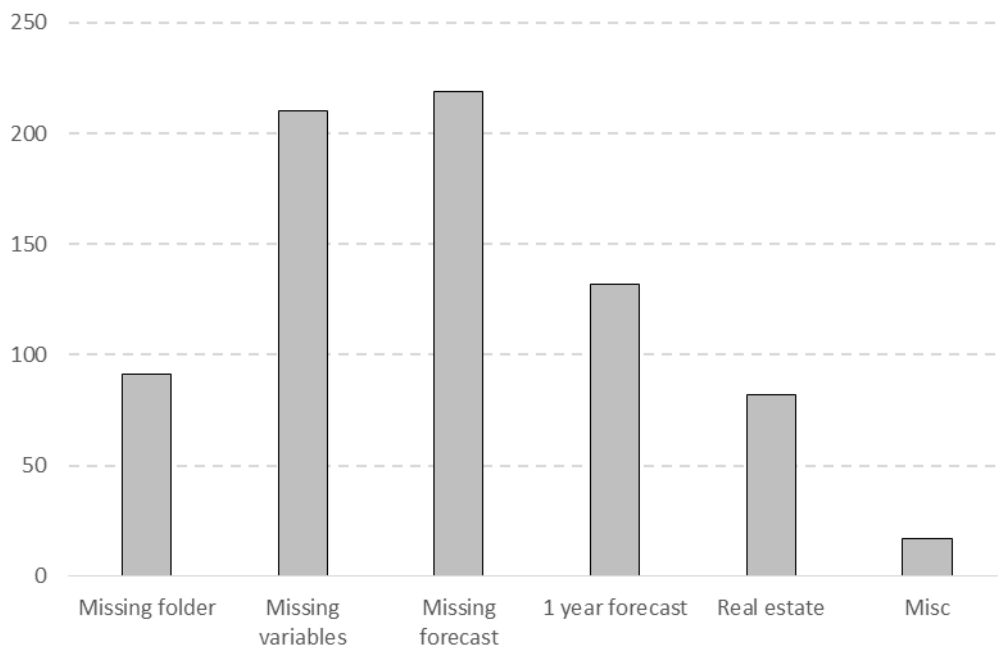
The black bar represent the initial sample and the grey bar, the final sample

The forthcoming section will further elaborate on the data gathering process and describe how transactions were excluded from the initial sample.

Missing data

From the initial 944 transactions, 91 were eliminated due to *missing folders* (an unavailable folder on the server). A further 211 transactions were due to *missing variables* (a folder consisting of inadequate amount of data). After further reviewing available folders an additional amount of 219 were eliminated due to *missing forecast* or *1 year forecasts*. *1-year forecasts* are those issued for the current financial year and stretched to the end of the accounting year. Since the exact issue date of the forecasts were usually unknown, these were partly influenced by actual outcome for that current year combined with a forecast for the remaining part of the year. This lack of transparency led to a decision to exclude them from the sample population. 17 transactions were excluded for other reasons, here labeled “Misc” such as when some companies were part of multiple transactions using the same forecast, or when the transaction was not really a transaction at all but some other type of project. Finally, 82 real-estate activities were left out, since revenues from rental income are relatively straightforward to forecast thus less relevant. Figure 6 shows respective categories for the first sample cut.

FIGURE 6. Sample cut 1

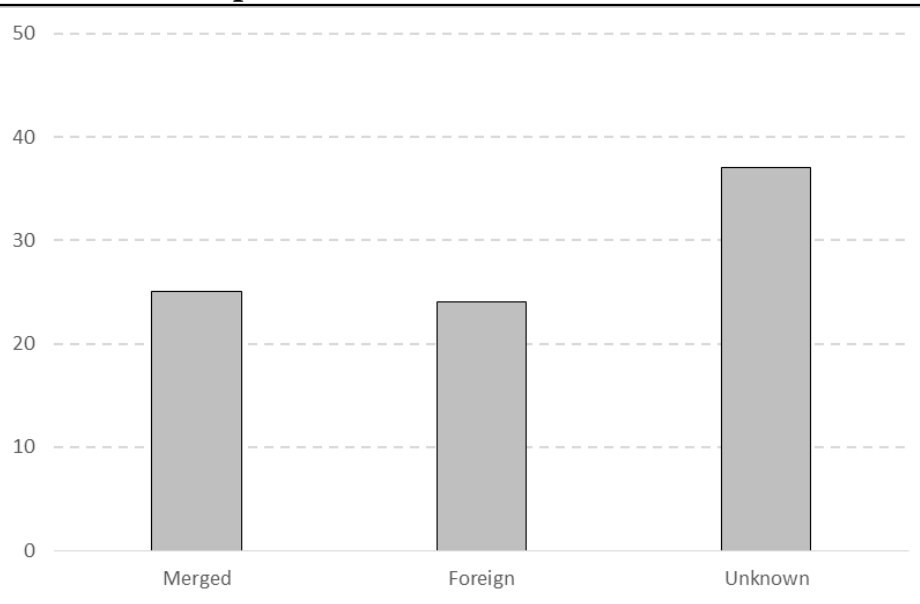


Sample cut 1 removed about 80% of the initial sample.

After the first sample cut, 193 transaction were left for further investigation. The remaining transactions were qualified for further review as they issued management forecast for at least two subsequent years but no longer than four years. The first exclusion was a result from the information in the internal database.

The second cut was a result of lacking information about historical revenues. There were three main reasons in this sample cut. Firstly, 37 unknown companies were eliminated due to unobtainable information. Occasionally, distinguishing items in financial statements made numbers difficult to interpret. Moreover, liquidated companies were also included in this category. Secondly, 25 completed transactions that had resulted in mergers and having data about revenues were nevertheless excluded. The reason was that their revenues were not representative since they included aggregated performance of multiple companies. Target companies were usually consolidated into the acquirer's organization, making relevant numbers unavailable. Thirdly, information regarding 24 foreign companies either could not be obtained or exhibited misleading numbers.

FIGURE 7. Sample cut 2



After sample cut 2, 89% of the initial sample had been cut.

The two sample cuts can be argued to be relatively extensive since approximately 89 % of the initial sample had to be removed. A larger final sample would be preferable to enhance the quality of the study and to increase the chances to finding statistical relevance to draw sound conclusions. Increasing the sampling frame may have been a possibility by getting additional access to physical archives. The “missing variables” and “missing folders” could be transformed into eligible transactions with inherent quality to be included in the sample. Unfortunately, these archives were not readily available and consequently were too expensive and time consuming to access.

The 103 potential transactions that remained constituted the final sample and is described further in the *Empirical Findings*.

Data analysis

The analysis can be thought of as a univariate analysis and a bivariate analysis – the first representing patterns in individual data sets and the second representing associations between variables. In general, the univariate analysis is described in the *Empirical Findings* and the bivariate part in the *Analysis*. Multivariate approaches could have been used to assess further relations between multiple variables but this is statistically more complex and requires deeper attention to such issues as multicollinearity and interactions. Spurious relations makes results from this approach much harder to interpret and likely does not add to the research but making it less transparent. It was therefore omitted.

Looking at the univariate analysis, the data itself came in different forms and thus entailed different approaches. The primary data was the forecast revenues and was coded as a ratio data type. This data was a part of the three dependent variables in this study with the first being the **forecast expectation** representing the mean forecast percentage growth over several years. Forecast expectation was used as an indicator of the overall sentiment of the forecaster and the firm, where a higher number would indicate a more optimistic outlook. This measure is thus reflecting the forecast without regards to the outcome. To account for this, the study used two measures of forecast performance. Specifically, **forecast bias** and **forecast accuracy** were used, each defined as the forecast error with respect to the outcome for the corresponding years. In the analysis, these three variables were calculated as the average for the first two years of the forecast i.e. the same year the potential transaction took place and the following year.

While forecast bias can be measured directly on the forecast errors, this study uses the percentage value to make better comparison across many different sets of data. However, percentages can be based on the first data point of the series, the preceding forecasted value, the preceding outcome, or even completely different variables. For example, Stunda (1996; 2000) scaled the forecast errors by the stock price, since his dataset was based on public companies listed on a stock exchange. In this study, the errors were based on the preceding forecasted value to capture the degree that forecasters expected to grow in percentage for every year, in comparison to their expected growth in the prior year.

For long time series, it may be useful to measure the median error. Here, the mean is used instead since the analysis is based on only two years of forecast i.e. two data points per time series. The purpose of analyzing bias is to capture the irrationality of the forecaster by understanding if there are consistent over- or underestimations. However, this does not consider the dispersion of errors. To account for both these factors forecast accuracy was measured as well. Accuracy can be calculated in many different ways e.g. using the absolute values, squared mean or the root-squared mean and be based on percentages or directly on the errors. There are also more complex variations by comparing the accuracy to benchmark methods or scaling the errors in various ways to avoid scale dependence, issues with infinite values etc. Appendix D describes a large number of these measures. The most common measure is calculated by the absolute value of the percentage errors which is also what is used here since it is arguably the most intuitive measure. The list of equations used is displayed below.

EQUATIONS. The main dependant variables used throughout the analysis

$$\text{Forecast} = f_t$$

$$\text{Forecast growth} = \frac{f_t}{f_{t-1}} - 1$$

$$(\text{Forecast}) \text{ Expectation} = \frac{1}{T-t} \sum_{t=1}^T \left[\frac{f_t}{f_{t-1}} - 1 \right]$$

$$\text{Forecast error} = \text{residual} = e_t = f_t - y_t$$

$$\text{Absolute forecast error} = |e_t| = |f_t - y_t|$$

$$\text{Forecast error percentage} = p_t = \frac{f_t - y_t}{y_t}$$

$$\text{Absolute forecast error percentage} = |p_t| = \left| \frac{f_t - y_t}{y_t} \right|$$

$$(\text{Forecast}) \text{ Bias} = \text{Mean Percentage Error} = \text{Mean}(p_t) = \frac{1}{T-t} \sum_{t=1}^T \frac{e_t}{y_t}$$

$$(\text{Forecast}) \text{ Accuracy} = \text{Mean Absolute Percentage Error} = \text{Mean}|p_t| = \frac{1}{T-t} \sum_{t=1}^T \left| \frac{e_t}{y_t} \right|$$

Note that Expectation is defined so that an optimistic outlook will result in a positive coefficient

Similarly, the forecast error equation is defined so that optimistic bias will result in a positive coefficient

Finally, accuracy is measured with 0 being a perfect forecast and larger values correspond to less accuracy

The three variables, expectation, bias and accuracy were analyzed by considering the central tendencies and measures of dispersion. More specifically, the mean and median, as well as the standard deviation and skewness were all considered essential to ensure proper understanding of the data distributions. Reasons for this resulted from the fact that many measures of data were highly skewed, causing a significant difference between the mean and the median.

The independent variables of size, financial condition, industry and business cycle were more heterogeneous. Most financial data were naturally coded as ratio data as well but industries represented category data type. Measures of the Swedish GDP percentage changes were measures as ratio data in this thesis. Yet, a different but viable approach would be to treat years as categorical variables and ignore the GDP changes altogether, which some researchers have done (Hsu, Hay, & Weil 2000).

The bivariate analysis generally took the form measures of correlation either through measuring the Pearson's R coefficient when analyzing sets of ratio data types, or through t-tests and one-way ANOVA tests when dealing with categorical variables. In some instances the Moods median test was used as a complementary tool when the data distribution was arguably less compatible to the former tests. Various kinds of tables and graphs such as contingency tables, line graphs, scatter plots and box-and whisker plots were used to display

the results throughout the report with the goal of highlighting the key takeaways from the tests and other forms of analyses.

Quality measures

This section will describe a series of measures used to describe the quality of the research and in particular, the quality of the results. To this end, the three common concepts within quantitative research are employed - reliability, validity and replicability. Each one of these can in turn be regarded from different angles. They will all be considered to provide a complete assessment of the quality of the thesis.

Reliability and replicability

First, reliability is assessed which describes the consistency of measures. A measure has strong reliability when it is consistent over time, for different indicators and for different observers. These three ideas are sometimes described as stability, internal reliability and inter-observer consistency (Bryman and Bell, 2011). Stability then, could here refer to consistency of measuring managerial expectation, bias and accuracy over different times. It can be considered very high in this research since there is little reason to expect the measures of this type to have a temporal restraint. While the results of measuring these over different time periods may differ on the basis that forecasting is dependent on the economic development, the measure themselves are unlikely to change. Similar arguments can be made for the other measures used. Measuring the business cycle based on GDP changes is unlikely to become irrelevant overnight. The measure of financial distress is partly based on a measure from 1980s, and is still relevant to date according to authors such as Wang & Campbell (2010), Kumar & Kumar (2012)

The internal reliability, which is whether multiple indicators are measuring the same thing, is expectable but with a few question marks. In general throughout this research, only one indicator and measure was used for each concept. For many variables, the indicator and the measure was the one and the same, since it was implicitly defined the way it was measured e.g. forecast bias and accuracy. However, for some indicators such as the GDP, it is only one measure of many for business cycles, others being unemployment rates, income levels etc. In the same way, firm size can be measured by the considering revenues (as done here), the book value or the number of employees. Financial conditions can also be measured in many ways and for this reason it may be the variable that has the most unclear reliability overall.

The inter-observer consistency regards the degree of consistency by the researchers about a variety of observations. This was not considered an issue since any disagreements could easily be verified through the data that was available at any point in time.

Regarding the replicability, it has been the authors' desire to maintain transparency to make it possible to replicate the study in detail. Consequently, the research process and the main steps in the data gathering, data processing and analysis, and in particular the sampling has been described comprehensively as a mean to this end. On the whole, seeing how the data is archival, easily codable, transferable and fairly objective, the replicability can also be considered high.

Validity

Validity may be the most important measure when gauging the actual conclusions of the report. It refers to the legitimacy of the concepts and whether they actually reflect what is intended. Whether the concept of bias and accuracy actually measure bias and accuracy is uncontroversial, although the four determinants can certainly be discussed. The four determinants chosen for this study are primarily based on their ease of measurability and the availability of data. Moreover, they have all been heavily researched in other studies and have been shown to be valid when evaluating forecast performance. Size and financial condition are indicators of the internal factors hypothesized to influence forecasters as explained in the literature review. However, there are certainly other indicators that can be used to cover different perspectives of a firm. Examples may be business strategy and organizational culture, which has been covered by previous researchers. Likewise, indicators of external factors are here chosen to be industry affiliation and the contemporary part of the business cycle. It is plausible that further external factors such as governmental regulations or geographic affiliation to be relevant as well. Thus, it is without question the case that the current determinants do not completely measure the full extent of what might possibly influence forecasters from an internal and external point of view. See table 2 for examples of a variety of determinants.

TABLE 2. Determinants and measures of forecast performance

Individual			
Profile	Prior forecast performance	Skills	
Gender	Average previous bias	# Years as forecaster	
Age		Education (Phd, Msc...)	
Internal			
Size	Financial condition	Business strategy	Diversification
Revenues	Ohlson score	Inventory turnover	Foreign sales ratio
# Employees	Net debt	R&D intensity	Foreign asset ratio
Book value	Debt ratio	Sales growth	
	Earnings volatility		
	Stock return		
External			
Industry affiliation	Business cycle	Geography	Input prices
SNI Categorization	GDP	Country	Energy costs
Level of concentration	Income levels		Rents
Industry lifecycle	Interest rates		

There are practically any number of potential determinants that can be used when analyzing forecast performance.
Note that the top row of each category represent the indicator and the italic text below possible measures of that indicator.

Another part of validity is internal validity, which evaluates the degree of causality that is or can be inferred from the research. This is fundamentally weak for a research of this type, since statistical tools typically are only able to measure correlation, unless every possible other influencing variable is controlled for. An issue here is the limited sample size, which made a probability sample less viable, further decreasing the validity since the sample may over-represent certain factors, observable or not. Generally, a probability sample deals with this issue by guaranteeing unbiasedness in the sample. Some temporal causation can be assumed because the data was taken from different time periods. In spite of this, it is generally unwise to make strong claims about causality between the dependent variables and the independent variables. It is possible that other, unobserved, variables are causing the correlations, rather than a direct relationship between the variables themselves.

External validity relates to the generalizability of the results from the research. In other words it questions to what degree the findings can be extended beyond the specific research context. Seeing how the data specifically came from M&A transactions, it cannot be assumed that the

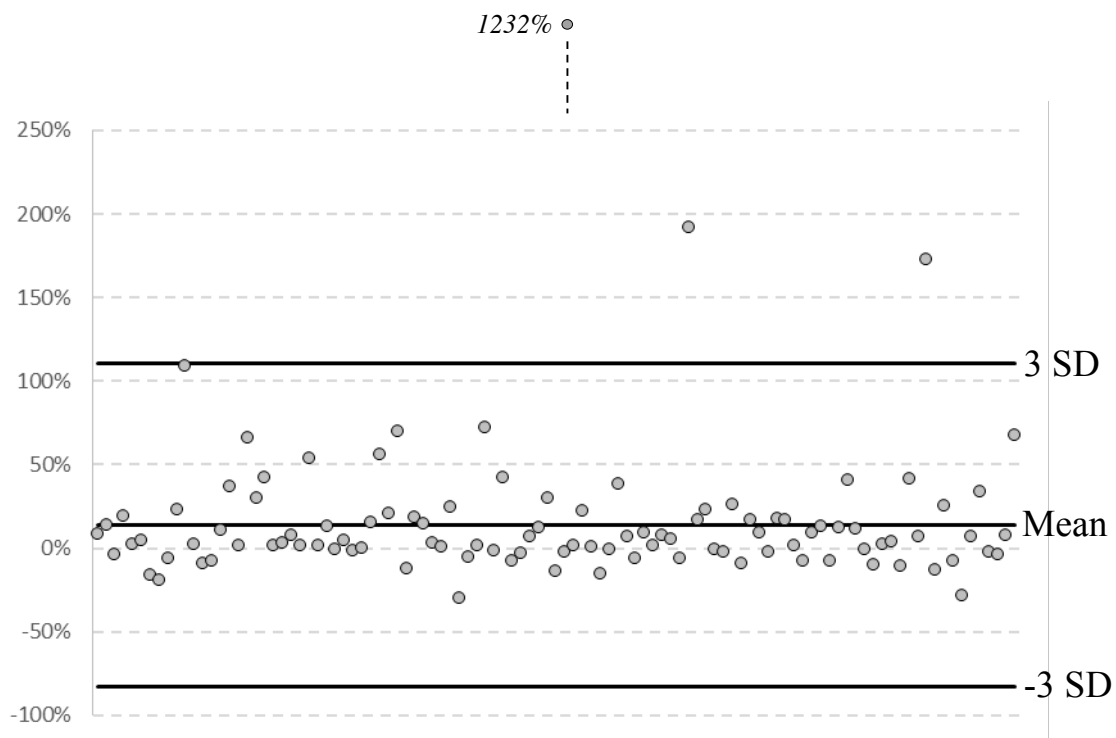
same result would hold for forecasts in other contexts. Within M&A however, the generalizability should be strong since the sample encapsulates a wide range of different companies, industries and over a considerable time period. The forecast behavior is a result of the incentives and psychology of the forecaster. Incentives may differ across countries and possibly to some degree over time (with changes in governmental regulations etc.). Psychological factors, and more specifically cognitive biases, should not change either over time or space (although a very long term evolution-based argument could be made here). As such, the external validity is considered high in the domain it was intended to for.

Finally, some authors mention ecological validity as measure of the closeness between the research and the real-life world. One important point can be made here – the overall arguments that M&A would generate incentives, which in turn would influence forecaster behavior is based on hypothesis from previous researchers and by understanding the M&A context. On this note, the authors might have gained a deeper understanding about the incentives by observing actual transactions and at a closer distance. Little is mentioned in this report about the transaction, the due diligence process, the stakeholders involved, the business valuation approaches and other factors that actually takes the forecast into consideration. For this reason, the ecological validity may seem weak at a first glance, but the relevance of the findings is there, even if not thoroughly explained here. See Appendix C for more info on these topics.

4. Empirical Findings

The final sample that was derived from the sampling process consists of multiple sources of data for each transaction. Primarily it is based on the revenues for the target three years prior to, and three years after the transaction, including forecasts for the later years. However, for the analysis of the determinants, only the year of the transaction and the year following was used due to the declining number of forecasts available after this point. The analysis also includes EBITDA and various data from the balance sheets to help estimate the financial condition for the target. Occasionally, there were missing values for individual data points such as lacking revenues for single years. In such cases, averages may not be fully accurate, but in general those were highly unlikely to make a significance difference overall. The missing values were in general treated as missing, that is, they were not estimated but simply skipped resulting in a smaller sample size for the specific calculation in question. In addition, another issue was dealing with outliers. Generally, many variables displayed high skewness as a result of a few numbers of extreme data points. Removing such outliers would bias the sample, but including them would cause misrepresentation of trends and findings for the various calculations used throughout the report. In the end, three selected outliers were removed, but the calculations generally included the mean, the median and skewness for every variable to make the difference transparent when certain “boundary” outliers were present. See Figure 8 for the data points representing the percentage forecast errors. The lines represent the mean and upper and lower limits for three standard deviations, which was used as the boundary conditions.

FIGURE 8. Distribution of forecast errors for final sample



Each dot in this figure measured the mean percentage forecast errors of the first two years.

All 106 transactions are included along the axis in no particular order.

Three of them were considered outliers and were left out in the subsequent analysis.

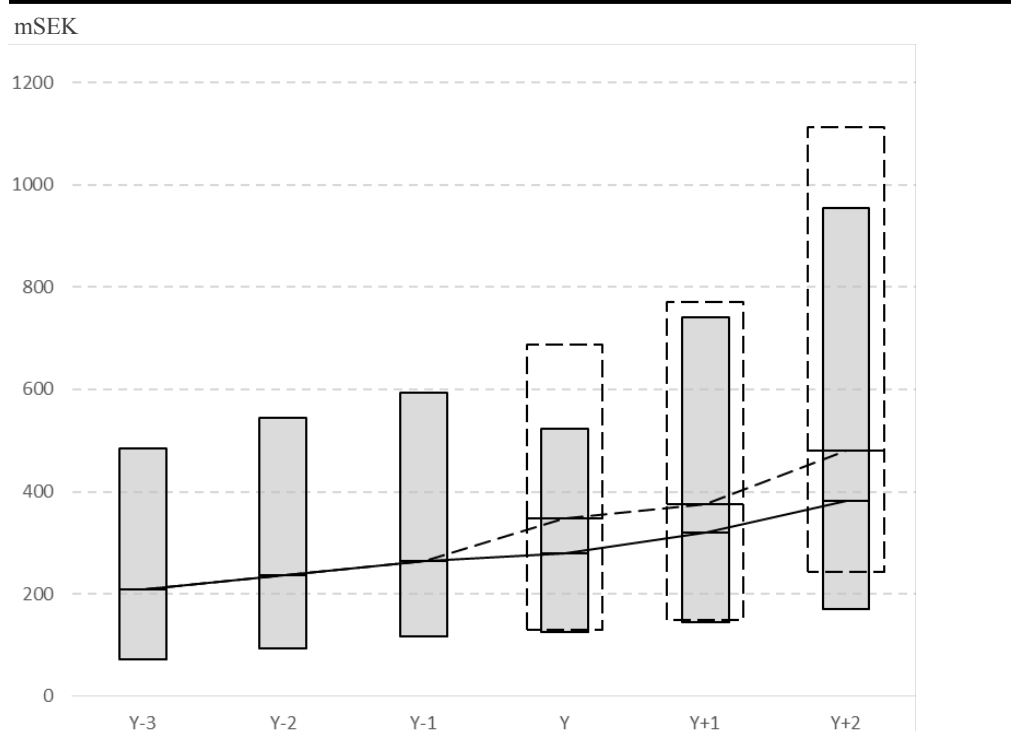
The bars represent the mean and three standard deviations in either direction.

Most of the calculations used percentages to facilitate better comparisons across different transactions. This is necessary since absolute values would make it unfeasible to compare smaller with larger companies. On the other hand, percentages tend to be high when approaching zero, causing issues when calculating accuracy and bias for very small companies that grows very quickly. There is, to the authors' best knowledge, no complete fair way of balancing when dealing with this issue, which is why most calculations had several measures and plots to facilitate better transparency about the data. In particular, given the strong skewness of the data, the median is in many ways a better representation than the mean since it is not influenced by extreme values to the same degree.

Figure 9 and Table 3 measures the revenues in MSEK three years prior to, and three years after the transaction, with year Y indicating the year when the transaction was initiated. The bars indicate the median and upper and lower quartile for the 103 transactions. Looking at Table 3 it is interesting to note that the targets have increasing revenues over time both prior to and after the transaction period. The forecasts, as indicated by the dashed bars and dashed

line, is consistently above the outcome. Initially, the data thus point to a degree of optimism and possible existence of bias. This can also be considered by looking at Table 4, which shows the direction of change for the companies based on their historical growth. Noticeable is that out of the companies that did not grow in the prior years, only about 30 percent actually turned it around, while 90 percent expected a turn around. Overall, about 33 percent did not grow after the transaction, but only 6 percent forecasted no-growth. More analysis on bias and accuracy will be dealt with in the *Analysis*.

FIGURE 9. Revenues - historical, forecast and outcome



The bars are the upper and lower quartile of revenues while the line represents the median.

The dashed bars are the forecast and the grey bars, the outcome.

Note that year Y is the year of the potential transaction and the first year the forecast was issued for.

TABLE 3. Revenues - historical, forecast and outcome

	Historical			Outcome, (forecast)		
	Y-3	Y-2	Y-1	Y	Y+1	Y+2
Min	1,4	2,1	4,3	4,5 (6,2)	6,9 (10,2)	5,0 (14,4)
Mean	622	651	694	729 (740)	796 (855)	971 (1118)
Median	209	237	264	280 (348)	320 (375)	382 (481)
Max	6099	5940	7282	8229 (7932)	9280 (8732)	9840 (9987)
StD	1154	1147	1215	1328 (1297)	1350 (1441)	1600 (1725)
Skewness	3,1	3,0	3,3	3,8 (3,8)	3,7 (3,6)	3,5 (3,2)

Revenues for the final sample over the years surrounding the transaction.

TABLE 4. Growth expectations and outcome

		Historical							
		Y	N			Y	N		
Outcome	Y	62	8	70		60%	8%	68%	
	N	21	12	33		20%	12%	32%	
Forecast	Y	79	18	97		77%	17%	94%	
	N	4	2	6		4%	2%	6%	
		83	20			81%	19%		

Y and N are short for Yes and No, signifying if a firm has/will experienced/forecast growth in the years prior to/after the transaction.

(1) Firm size

Firm size is measured as the average revenue three years prior to the issue of the forecast. The revenue for the year prior to the forecast issue may arguably be the most appropriate number used to express firm size. However, the average measure is also considering potential fluctuations over years and alleviates potential extreme values. Yearly accounting techniques and other actions may also result in misleading numbers when only expressing firm size based on one-year revenue. Based on these arguments, a three-year average revenue was used for each company. Other measure such as capital structure, assets and employees are also common when expressing firm size. However, since this study is structured around revenue forecasting, this measure was considered the more appropriate one to use.

Statistics Sweden has established a standard for categorizing companies based on both revenue and number of employees. It contained four groups ranging from micro to large firms. This study aggregates micro and small companies into the same category since the micro category only contained four transactions. Table 5 below shows that just below 50 percent of the transactions consisted of Mid-size firms and the remaining ones were fairly distributed over small and large firms. *n* refers to the number of transactions in each respective category in the final sample. Nevertheless, the sample addresses the range from small to large firms. However, no firm is included in the Swedish top 100 largest companies (minimum 10 billions SEK) nor are micro firms not extensively investigated. Additionally, this standard has been used to be consistent with additional classification of industries also used by Statistics Sweden.

TABLE 5. Firm size classification

	Revenue	Employees	<i>n</i>
Micro	<19	<9	4
Small	20-99	10-49	23
Medium	100-499	50-249	50
Large	>500	>250	26

The classification used in this study was based solely on the revenues.

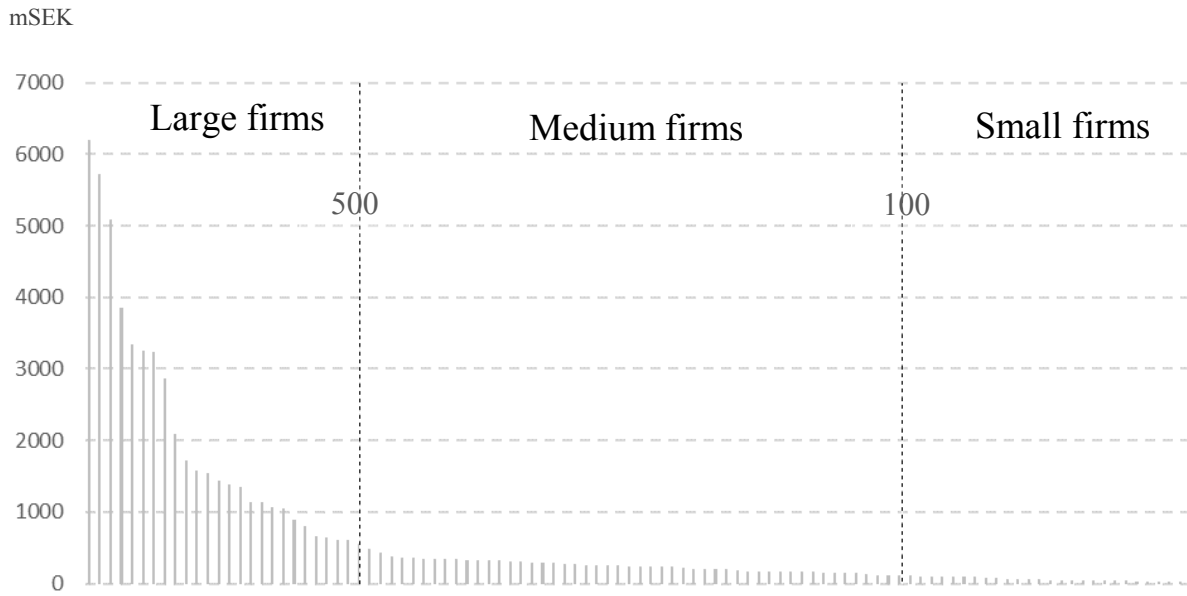
The argument is made that using revenues as a metric of firm size is superior to the one of employees since they tend to fluctuate after completed M&A. This basically means that employees are transferred between acquirer and the target company during the integration process, which takes place after the transaction is completed. Additionally, firms tend to transfer employees between companies making this metric hard to evaluate. Descriptive statistics regarding firm size can be found in Table 6.

TABLE 6. Historical mean revenues

Mean	Median	SD	Max	Min
651	232	1160	6182	3

Median revenues are approximately 232 MSEK since 50 percent of the transactions are Mid-size firms. However, the extensive standard deviation (SD=1160 MSEK) indicates a positive skewed distribution of revenues as the average company's revenue is 651 MSEK. The high skewedness can be explained by a few large companies being exceptionally large compared to the rest of the sample (25 percent), which likely reflect the population at large. The largest and smallest company had average revenue of 6182 MSEK and 2.6 MSEK respectively and thus reflect a broad range in this variable. Looking at Figure 10 shows the distribution of small, medium and large companies. The vertical lines in the diagram indicates the size classification applied in this study. As a result, one can interpret the companies to be fairly equally distributed across small, medium and large firms.

FIGURE 10. Revenue distribution



This figure illustrates all transactions in order of size measured as the average historical revenues for the three years prior the transaction year.

(2) Financial condition

Three methods have been used to determine the financial condition of a firm, *net debt*, *debt ratio* and *Ohlson's O-score equation*. This section will describe these metrics and its usages applied in this study. Moreover, empirical result about the degree of financial distress will be presented.

Measures of financial condition are multifold and can be calculated using different types of metrics depending on the preferred time horizon, context or decision. Measure such as cash liquidity is only considering the short-term obligations for companies, while solvency is taking on a longer time horizon. Other measurements such as risk of bankruptcy, debt ratio and net debt are also commonly used in finance to estimate the financial condition of a firm. Net debt may be the most commonly used measure among practitioners, which motivates its usage (Manager, KPMG). Net debt calculates the relationship between financial debt and EBITDA and gives information about how long it takes to payback the interest bearing liabilities.

$$\text{Net Debt} = \frac{\text{Interest bearing liabilities} - \text{Cash and Bank}}{\text{EBITDA}}$$

The alarm ratio differs across industries, making this measure hard to interpret without industry specific information. Therefore relationship between higher net debt and forecast performance will be analyzed to determine if increasing net debt is associated with more

optimistic forecasts. A negative net debt is an indication of a company possessing more money than debt. Nevertheless, an argument speaking in favor of using this measurement is its ability to capture the years it would take to pay back a company's loan given that EBITDA is held constant.

Debt ratio is relatively straightforward to calculate and is simply the relationship between total debt and equity. Like net debt it is very common financial measure. It basically indicates how much of a company's assets that are financed by its debt. Capital-intensive industries such as automobile companies tend to a higher degree of debt ratio compared to for instance, personal computer companies where less capital is required. In contrast to net debt, earnings are not considered in favor of equity securities. Both these measures are therefore interesting as they are considering different aspects of financial risk.

$$\text{Debt Ratio} = \frac{\text{Total liabilities}}{\text{Equity}}$$

The O-score developed by Ohlson (1980) is one of the most common measures used in research to predict bankruptcy of firms within two years and is argued to be a measure of financial distress. The formula is based on nine business ratios and is essentially an equation based on assets, liabilities, net income, net loss, working capital and funds from operations (FFO). All these measures are easily obtained from firms' financial statements. Yet firm size is expressed as a natural logarithmic relationship between total assets and GNP based on price index, which is the only external metric that is not firm specific. FFO is gathered from cash-flow statements before changes in working capital. Extra ordinarily transactions have also been excluded to accurately reflect cash flow from operations. The formula can be obtained in Appendix F where a more comprehensive description of its usage can be found. After the calculation has been made, the O-score is converted into a probability of bankruptcy. Table 7 below shows average/median net debt, debt ratio and O-score plus complementary statistics for the final sample.

TABLE 7. Measures of financial condition

mSEK			
	Net debt	Debt ratio	O-score
Min	-8.6	-6.0	0%
Mean	0.8	4.9	13%
Median	0	2.1	4%
Max	33.8	75.8	100%
StD	4.6	9.5	23%

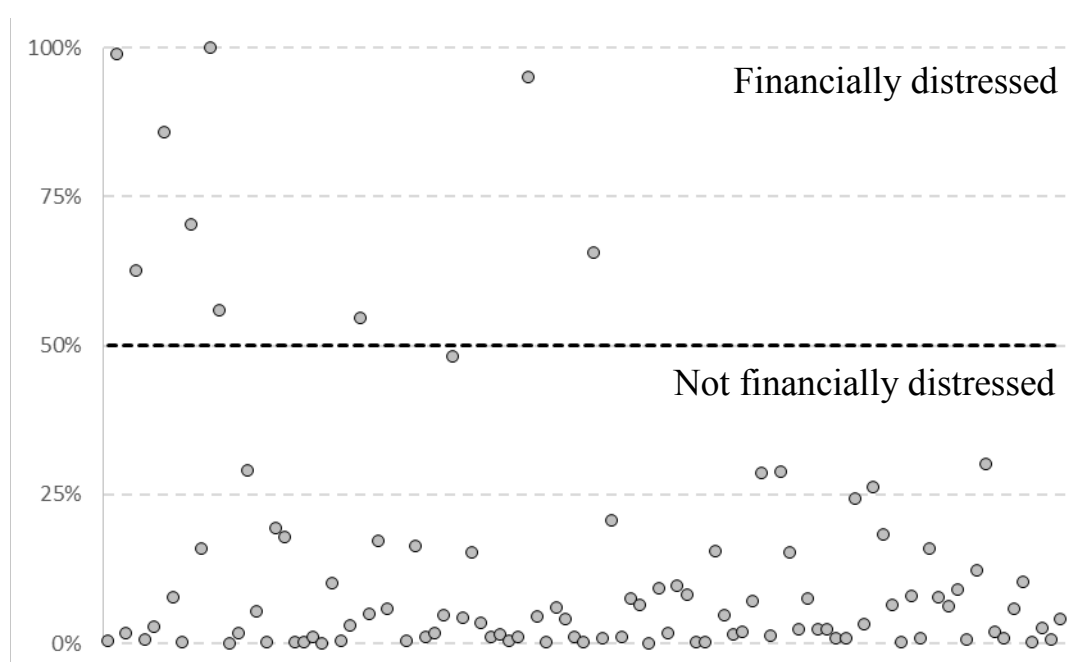
See Appendix F for more information of O-Score

Both mean net debt and debt ratio are calculated as an average of three years prior to the issued forecast and adds up to 0.8 vs. 4.9 for the final sample. According to these numbers, firms were on average not financially distressed (net debt less than factor 4). However, the quality of financial statements varied making interest-bearing liabilities occasionally hard to interpret even though they existed. Consequently, many companies displayed no interest-bearing liabilities, resulting in lower values overall.

Both net debt and debt ratio differs across industries making it difficult to specifically set an interval for when a company is perceived as financially distressed. Instead, the authors' desire was to identify relationships between these measures and the forecast performance and to identify pattern of deviations compared to the rest of the sample.

Shifting focus towards Ohlsons O-score showed that the average risk of going bankrupt within two years was 13 percent. It should also be noted that the median probability of bankruptcy was generally low at 4 percent. Surprisingly, some firms exhibited extensively high probability close to 100 percent. On the other end, several healthy firms exhibited almost no probability of going bankrupt. The probability distribution can be found in Figure 11, below.

FIGURE 11. **Distribution of O-score**



Each dot is the O-score for the corresponding transaction. This measure predicts the chance of bankruptcy within two years.

Reflecting upon the mean (13 percent) showed that the majority of firms' probabilities of going bankrupt were within the range of zero to twenty percent. According to Ohlson (1980), a probability under 50 percent is representing a non-failing company, while firms with a probability above 50 percent are predicted to go bankrupted within two years and are consequently financially distressed (Mitchell & Walker 2008). Consequently, shown in Figure 11, nine companies exceeded 50 percent and were perceived to be financially distressed according to this measure.

(3) Industry classification

An unequal distribution of transactions across industries made it necessary to aggregate industries. It was the desire to draw conclusions about every SNI sector (see Appendix E). The small sample size hampered the ability to draw any conclusions regarding bias across finer industries. Three industries are dominating the final sample and the remaining ones are not sufficiently large to draw conclusions, therefore aggregations had to be considered.

Aggregation of industries can be made in several ways by analyzing a wide range of input factors such as revenue volatility, industry growth, value chain position, market shares, tangible activities, operational areas etc. But when the number of and input variables increases so does the complexity and potential combinations. However, facilitating the aggregation was

perceived necessary both to minimize the number of input variables. Five industry aggregations were established based upon similar company characteristics explained below. Table 8 illustrates the aggregated industries and the number of transactions in each respective category.

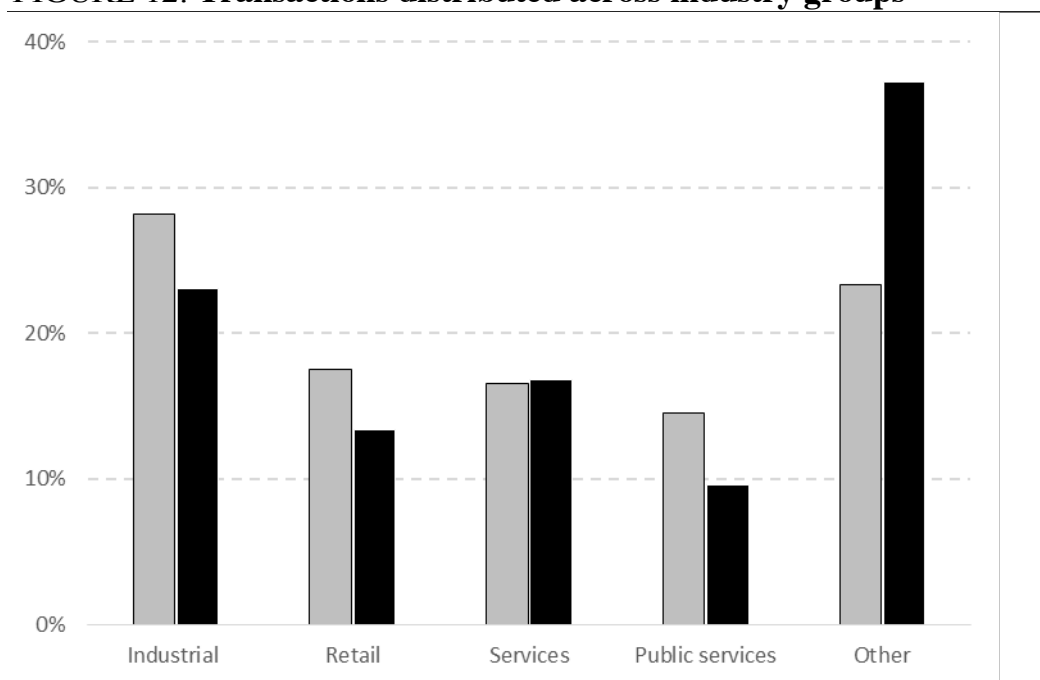
TABLE 8. Industry groups

	Industrial	Retail	Services	Public services	Others
SNI	C	G	KMN	QP	FHJ
<i>n</i>	32	18	17	15	21

The largest category was *Industrial* (manufacturing and producing companies), which included industry C. The second largest were *retail* (G) comprising of companies selling product and complementary services but not necessary manufacturing them. The third largest category, *Services* (K, M and N), were companies providing some kind of service, this includes financial and insurance activities, scientific and technical activities and support service activities. They were mainly providing some kind of professional knowledge. The fourth largest category were *public services* (Q and P, referring to Human health and human work activities, and education) which were combined since their performance are based on fundamental needs with less fluctuating demand. Lastly, the remaining companies (F, H and J) were aggregated since no evident relationship to any other category was found.

The new classification system was now more fairly distributed compared to the initial one presented in the sampling section. As was initially described earlier, some companies operated in several industries (i.e. both manufacturers and retail), which could create obstacles for comparisons. However, the most eminent one was used through assessment of the companies' financial statements when such uncertainty existed.

FIGURE 12. Transactions distributed across industry groups



The black bar represent the initial sample and the grey bar, the final sample

(4) Business cycle

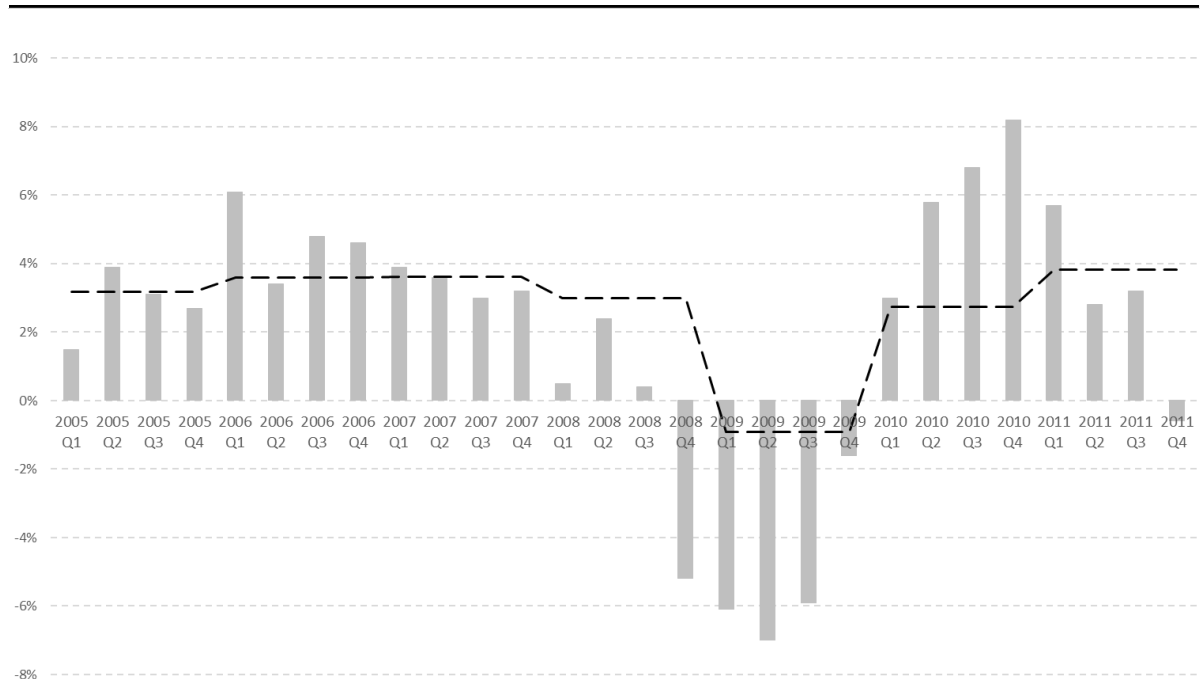
There are multiple ways of measuring the effect of the economy as a whole by observing changes in unemployment rates, inflation, income levels, stock indexes and other macroeconomic indicators. In this study, the GDP expenditure indicator was used which is an easy interpretive and all-compassing measure of the overall economic activity since it typically exhibits the cyclical feature expected during downturns and upturns. In particular, quarterly percentage changes to the corresponding period previous year in the Swedish economy at market price was used with data taken at each quarter between 2005 and 2011. The GDP is measured at multiple occasions as additional information became available. Here, the data was collected from *Statistics Sweden* with the most recent numbers used for such quarterly GDP outcomes to ensure maximum accuracy. While a small part of the sample consisted of Nordic, non-Swedish firms, they were few and it is safe to say that similar economic forces took place in these neighboring countries. Thus, the effect of the business cycle on the management forecast can be expected in these firms as well, if any. Fortunately, the years between 2005 and 2011 had periods of both strong growth and serious decline during the 2008 financial crisis, which gave the favorable opportunity to observe changes through an entire business cycle.

Analyzing the GDP outcomes with management forecasts would facilitate understanding whether the current state of the economy influenced the forecasting process. In addition, a number of institutions, banks and other organizations in Sweden also issue macro-economic forecasts. The more well-known organization is the government agency National Institute of Economic Research (Konjunkturinstitutet) who issues GDP forecasts four times a year where they estimate GDP levels in the current-and upcoming year. Forecasts corresponding to years 2005-2012 have been collected and summarized in Figure 13. Using these forecasts made it possible to understand the degree of outlook on the macro economy and if it influenced forecasting at firm level. Moreover, comparing forecast errors between macro-economic forecasts and management forecasts made it possible to deduce whether forecast bias were a result from external factors rather than internal factors or vice versa. Such forecast errors could be calculated similarly to the management forecasts by taking the percentage differences for each year.

As Figure 13 demonstrates, the GDP dropped in 2009 but quickly regained a positive growth in 2010. The Swedish economy had an average of 1.7 percent growth during this period, partly explaining the general revenue growth in the sample used in this study. It also vaguely follows the cyclical pattern expected during a full business cycle. Looking at the forecasts issued the quarter prior to the forecasted year, it appears that they are generally less extreme than the actuals, with a standard deviation of 1.5 percent compared to 3.5 percent for the actuals, resulting from both positive and negative errors. Table 9 also shows the two-year forecast, which shows even less fluctuations with a standard deviation of 0.4 indicating the difficulty to forecast longer horizons. Both one and two year forecasts also appears to exhibit optimistic bias with an average projection of 2.7 percent over the entire period.

Table 9 also provides the error in percentage points for one and two year forecasts respectively. As expected, the errors are larger for two-year forecasts and the most crucial errors seem to occur during the years of the financial crisis. Not surprisingly since those years had the most rapid changes in GDP during the investigated period.

FIGURE 13. GDP Outcome and GDP Forecast



The quarterly GDP as a percentage of previous year are shown in the bars for the analyzed time period.

The GDP forecast as issued by the National Institute of Economic Research are shown in the dashed line.

This forecast was issued one quarter prior to the year it forecasted and thus represented the most recent information available.

TABLE 9. GDP Forecasts, outcome and errors

% growth

Forecast	2005	2006	2007	2008	2009	2010	2011	MEAN	SD
Y-1 Q4,1	3.2%	3.6%	3.6%	3.0%	-0.9%	2.7%	3.8%	2.7%	1.5%
Y Q1,1	3.0%	3.7%	3.9%	2.5%	-3.9%	2.4%	4.2%	2.3%	2.6%
Y Q2,1	2.1%	3.8%	3.6%	2.4%	-5.4%	3.7%	4.4%	2.1%	3.2%
Y Q3,1	2.4%	4.1%	3.5%	1.7%	-5.0%	4.3%	4.3%	2.2%	3.1%
Y Q4,1	2.7%	4.3%	2.7%	0.8%	-4.4%	5.6%	4.5%	2.3%	3.1%
Y-1 Q4,2	2.8%	3.1%	3.2%	2.8%	1.9%	3.3%	2.9%	2.9%	0.4%
Y Q1,2	2.9%	3.2%	3.4%	2.6%	0.9%	3.8%	3.1%	2.8%	0.9%
Y Q2,2	2.8%	3.2%	3.7%	2.0%	0.8%	3.0%	2.9%	2.6%	0.9%
Y Q3,2	2.9%	3.3%	3.8%	1.4%	1.5%	3.4%	1.9%	2.6%	0.9%
Y Q4,2	3.6%	3.6%	3.0%	-0.9%	2.7%	3.8%	0.6%	2.3%	1.7%
Outcome									
Q1	1.5%	6.1%	3.9%	0.5%	-6.1%	3.0%	5.7%	2.1%	3.8%
Q2	3.9%	3.4%	3.6%	2.4%	-7.0%	5.8%	2.8%	2.1%	3.9%
Q3	3.1%	4.8%	3.0%	0.4%	-5.9%	6.8%	3.2%	2.2%	3.8%
Q4	2.7%	4.6%	3.2%	-5.2%	-1.6%	8.2%	-0.6%	1.6%	4.1%
	2.8%	4.7%	3.4%	-0.5%	-5.2%	6.0%	2.8%	2.0%	3.5%
Error									
1 Year	0.4%	-1.1%	0.2%	3.5%	4.2%	-3.2%	1.0%	0.7%	2.4%
2 Year	-1.9%	-0.3%	3.7%	7.9%	-4.1%	0.5%	2.9%	1.3%	3.7%
	-0.8%	-0.7%	1.9%	5.7%	0.1%	-1.4%	2.0%		

The forecast table refers to "forecast issue period, year forecasting". For example, the first value (3,2) in row Y-1 Q4,1 and column 2005 refers to the forecast issued the fourth quarter of 2004 of the GDP for year 2005.

1 Year, and 2 Year in the error table are the errors for year 1 and year 2 respectively

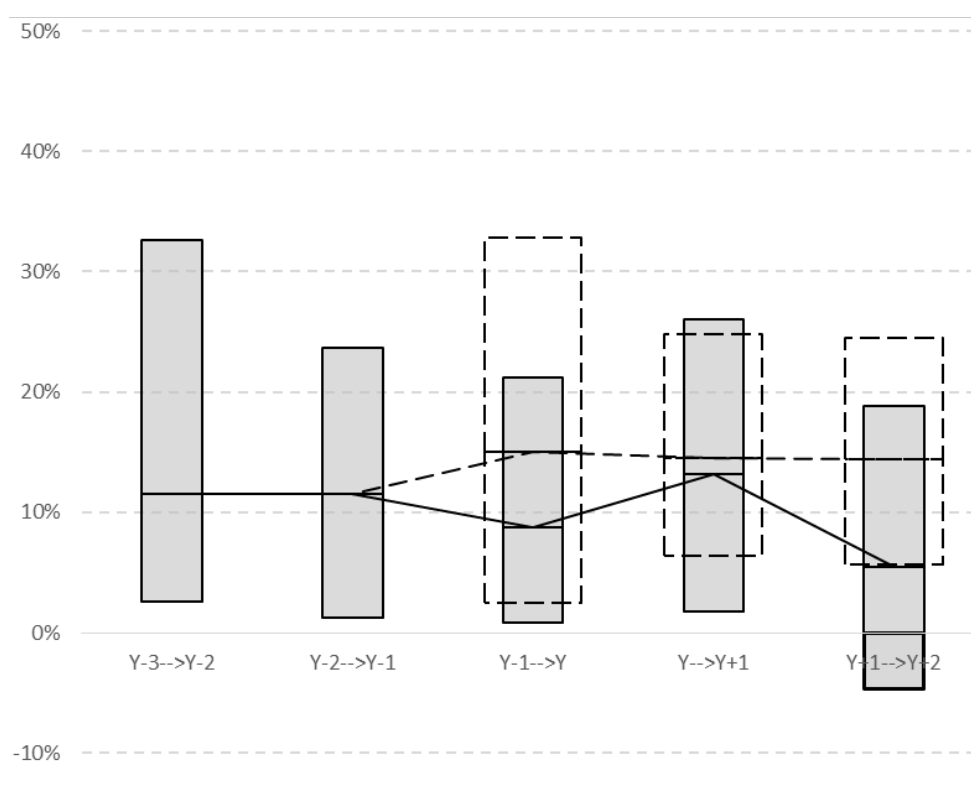
5. Analysis

This section analyzes the forecast performance over the final sample with respect to the determinants and corresponding hypotheses. Three main variables will be taken under consideration for each section, the expectation representing the expectations of growth, bias signifying the direction of forecast errors and accuracy, measuring the size of the forecast errors. Each variable is taken at the average for the first two years when analyzing the determinants. In addition, multiple statistical tests will be carried out, and according to the customs of statistical analyses, a p-value less than 0,05 is considered a significant result. Findings will also be discussed in this section.

Figure 14 and Table 10 shows percentage changes of revenues, both forecasts and actuals. In other words, they demonstrate the change from one year to the next. Looking at the figures indicate the suspected optimism. In particular, it is interesting to note that the median growth in the years prior to the transaction year was about 12% while the forecasted values was closer to 15%. The expectation was 20%, meaning that companies estimate on average 20% growth in revenues between years following a transaction. Also, the actual mean growth was consistently above 4%, which is according to Statistics Sweden (2015) the average annual revenue growth for all Swedish companies during the period 2002-2013. Hence, target firms in this study did on average represent a higher growing sample than the Swedish market at large. A gap can be noted in the year $Y-1 \rightarrow Y$ between the forecast and outcome, which is somewhat narrowed in the subsequent period. This may indicate that companies that did merge or become acquired would not have realized any large growth directly following the transaction but caught up later on. One possible explanation is that expected revenue synergies take time to ensue.

The minimum forecasted growth is also decreasing for every year and not a single firm estimate negative growth in three years ahead (the minimum expectation being 2%). In general, the outcomes varies more after the potential transaction compared to the historical figures which may be a result of actual M&A taking place and disrupting the business of the firms in both positive and negative ways.

FIGURE 14. Revenues - percentage change in historical, forecast and outcome



The bars are the upper and lower quartile of percentage difference in revenues between two subsequent years

The dashed bars are the forecast and the grey bars, the outcome.

The line represent the mean for the outcome (solid) and forecast (dashed)

TABLE 10. Revenues - percentage change historical, forecast and outcome

	Actual, (forecast)									
	Y-3-->Y-2	Y-2-->Y-1	Y-1-->Y	Y-->Y+1	Y+1-->Y+2					
Min	-43%	-57%	-43%	(-27%)	-43%	(-5%)	-46%	(2%)		
Mean	38%	20%	14%	(20%)	16%	(20%)	7%	(19%)		
Median	12%	12%	9%	(15%)	13%	(15%)	5%	(14%)		
Max	1018%	191%	159%	(129%)	131%	(114%)	63%	(99%)		
SD	113%	37%	26%	(27%)	27%	(20%)	19%	(17%)		
Skewness	699%	218%	203%	(120%)	123%	(185%)	-7%	(196%)		

Table 11 denotes the measures of performance - accuracy and bias. These two measures are also graphed out in Figure 15 and Figure 16. Again, the bars in the figures capture the median and upper and lower quartiles from the sample. The suspicions of bias can be confirmed by noting that the bias was estimated as 17 percent across the three years. In other words, companies overestimate their revenues by 17 percent on average. Interestingly, Figure 15 shows how bias is increasing for every passing year. It is worth mentioning that Year Y was

not one-year-ahead forecast but rather 0-12 month varying for each potential transaction depending when it took place in the given year. This would explain the lower bias for Year Y compared to Year Y+1 and Y+2. The standard deviation in the sample was 33 percent on average, indicating that the forecast bias differed vastly for each transaction and company.

In order to understand the value of the forecasting process, the bias can be compared to the naïve model of a random walk. This measure takes the simplest forecasting approach by forecasting the previous year's value for every subsequent year. Using this approach and calculating the bias turned result in -11, -34 and -44 percent for year Y, Y+1 and Y+2. The bias were in other words pessimism. This can be expected since the average company grew and the naïve forecast assumes no change from the last recorded year (Y-1). To compare, the mean bias discovered in managers forecast were 7, 14 and 31 percent over the same years.

Look at the accuracy, it can be seen to be worse for every year as well indicating the difficulty over forecasting over longer time horizons. The similarity of the figures were derived from the fact that the absolute of a positive number is the same, and due to the considerable optimism in the sample, the numbers were in many cases the same. Using a naïve approach for the accuracy led 22, 39, and 49 percent for Year Y, Year Y+1 and Year Y+2. Managers had an accuracy of 12, 22 and 36 percent over the same years. This indicated that managers do create some value relative to the pure mechanical approach of the naïve forecasts. Note that while the accuracy shown here is in its untransformed form, the later sections used the natural logarithm to ensure better fit to the normality assumptions that generally facilitate better matching with the statistical tools used. Figure 17 demonstrates the accuracy untransformed and transformed and compares the data to a “perfect” normal distribution.

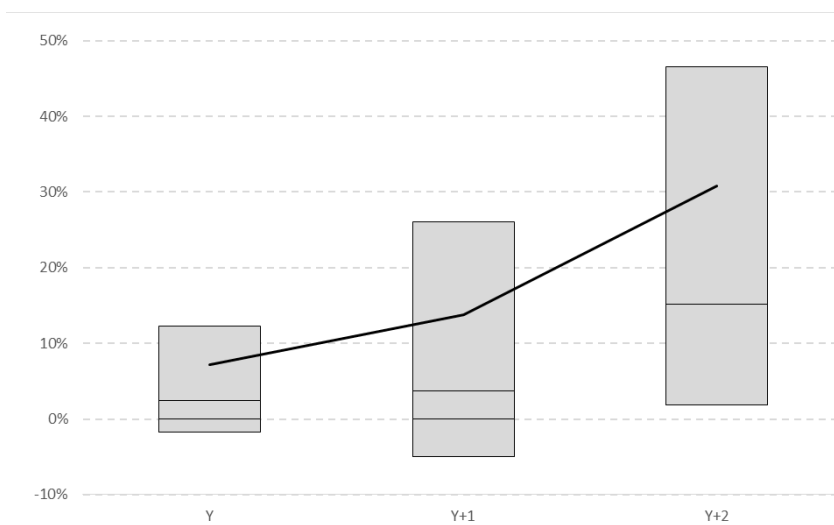
For both the bias and accuracy, the mean was significantly higher than the median. This was the result of some firms exhibiting considerably worse accuracy (equivalently very high values of accuracy), making the sample skewed. These “outliers” were partly a result of the usage of percentages creating an inherent bias towards smaller companies, where small changes caused large percentage changes. For this reason it may be reasonable to use the median in this case instead.

TABLE 11. Forecast performance

	Forecast error				Absolute forecast error			
	Y	Y+1	Y+2	MEAN	Y	Y+1	Y+2	MEAN
Min	-31%	-32%	-23%	-28%	0%	0%	0%	0%
Mean	7%	14%	31%	17%	12%	22%	36%	23%
Median	2%	4%	15%	7%	6%	14%	19%	13%
Max	96%	140%	225%	154%	96%	140%	225%	154%
SD	19%	31%	48%	33%	16%	26%	45%	29%
Skewness	174%	162%	206%	180%	249%	225%	241%	239%

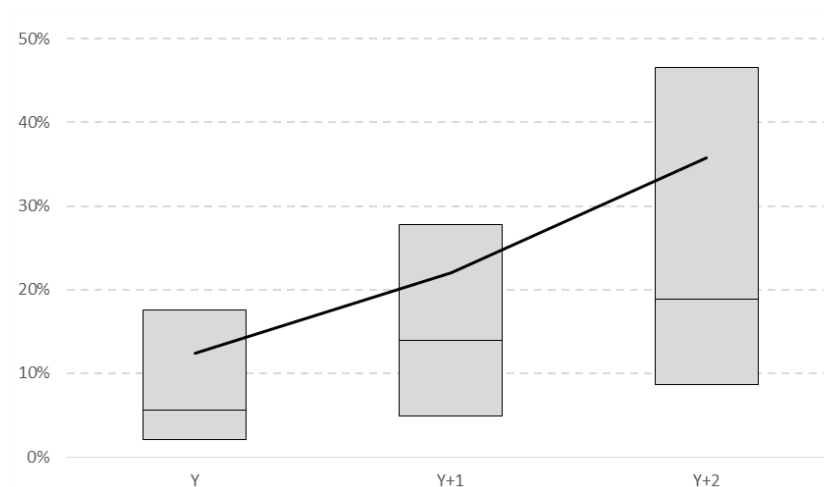
The forecast errors and absolute forecast errors are used to assess the bias and accuracy, which is calculated as the mean (or median) over the three years.

FIGURE 15. Forecast Bias



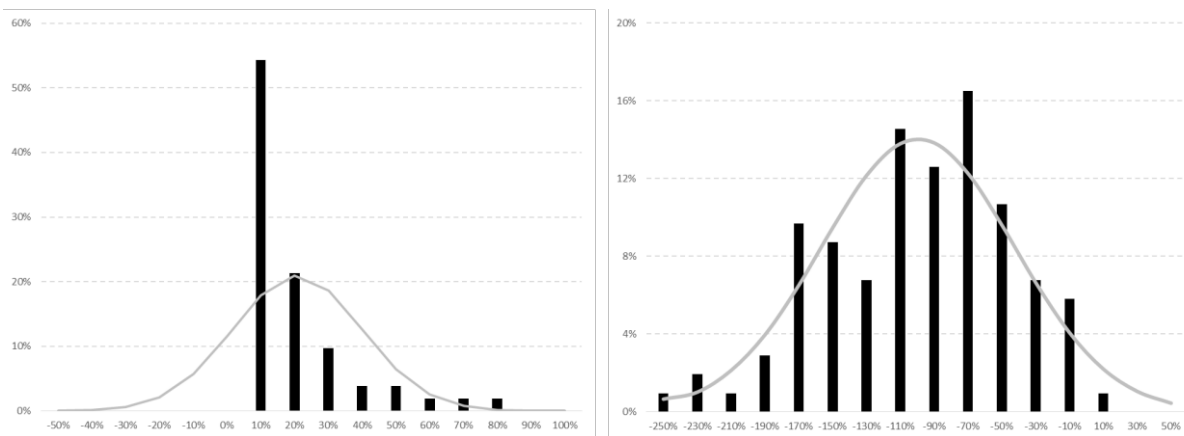
The bars are the upper and lower quartile of percentage errors with the median in the middle. The line shows the mean over the same period. The positive and upward trend of the mean and median suggests optimism and bias.

FIGURE 16. Forecast accuracy



The bars are the upper and lower quartile of absolute percentage errors with the median in the middle. The line shows the mean over the same period. Larger errors are observed for every year indicating less accuracy for a longer forecast horizon.

FIGURE 17. Transformed and untransformed forecast accuracy distribution



The black bar represent the transformed observed accuracy while the grey again represent what would be expected if the data was perfectly normally distributed

Reflecting upon the results so far it is noteworthy that the firms exhibited optimistic bias. Müller (2011) who analyzed undisclosed revenue forecasts argued that fewer incentives existed when forecasts were not disclosed. This is interesting since it may be argued that forecasts issued during M&A are still undisclosed to market and should not have exhibited extensive bias according to the findings of Müller (2011). However, these forecasts could partly be perceived as disclosed since they were presented to potential buyers where certain incentives probably existed. Building on this argument, one may argue that these forecasts were influenced by incentives, with the argument of receiving a higher premium paid for the company or other personal gains. But since this cannot be confirmed in this study, further research has to be carried out in order to confirm these ideas.

(1) Firm size

Optimistic bias is expected to prevail in forecast issued both by smaller and larger firms. The *Empirical Findings* indicated a fairly distributed amount of companies divided into small, medium and large firms.

The data has mainly been analyzed through linear correlations to identify significance between firm size, expectation, bias and accuracy. As shown in Figure 10, a positive skewness existed as a result of the large discrepancy of company revenues. Similar to earlier research (Hsu, Hay, & Weil 2000), the natural logarithm has been used to transform revenues to decrease the variation between large and small companies. Consequently, this made the values more linear and made size more normally distributed. Similarly, the standard deviation for revenues three years prior to the transaction were divided by the average revenues to express the volatility in revenues independent of firm size. This created the opportunity to

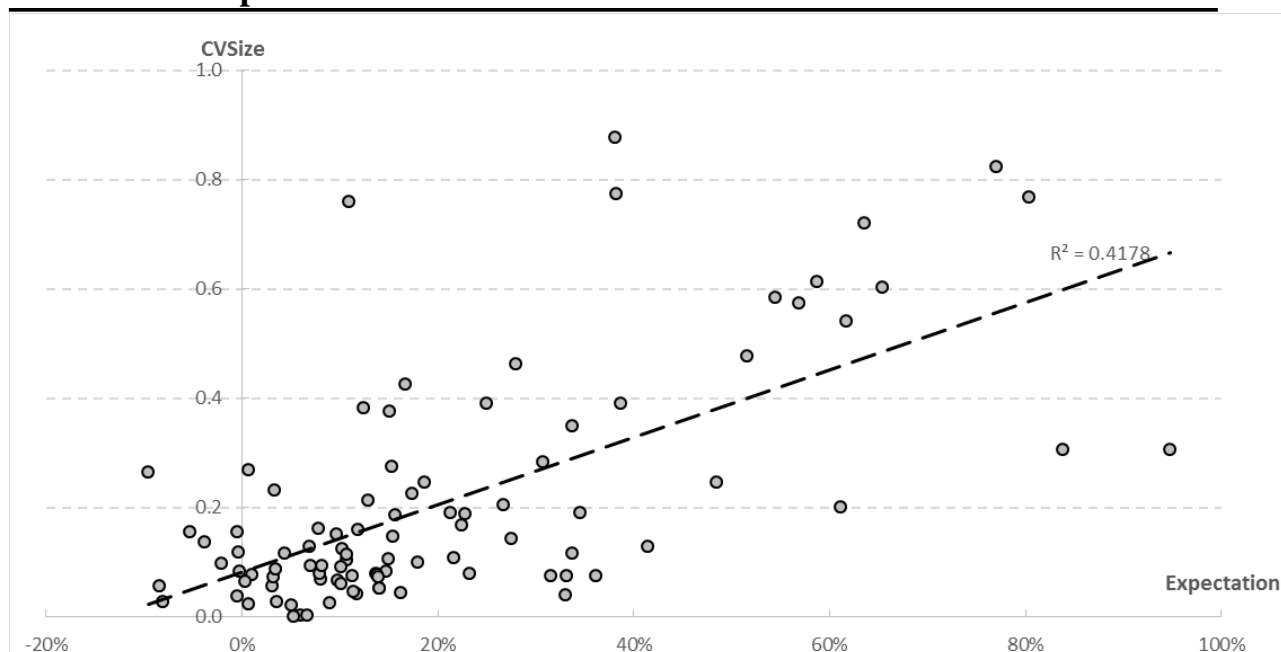
find relationships between bias and volatility in revenues independent of firm size. This is henceforth called the CVSIZE.

$$\text{Coefficient of variation} = \frac{\text{Standard deviation}}{\text{Mean}}$$

Figure 18 below shows the relationship between expectation and the CVSIZE. Studying the figure reveals that higher variation in revenues is linked to higher expectation. An unadjusted coefficient of determination (R^2) of 0,42 basically means that the linear model explain 42 percent of the variation in expectation and CVSIZE.

Looking at Table 12 it appears that smaller companies with low average revenues have higher expectation. Consequently, small companies are on average expecting to grow more for the three subsequent years after the initiated transaction when measuring the expected growth in percentage. Several of the smaller companies are expecting their revenues to increase substantially as the expectation is within the interval of 150-200 percent. An explanation for this behavior could be that it is generally more plausible to double a small revenue compared to a large revenue. Additionally, larger companies are usually diversified and compete on fundamental markets where customers are well known and revenues less volatile. On the contrary, smaller firms may participate in markets where information is sufficient to issue accurate forecasts.

FIGURE 18. Expectation and Coefficient of Variation in size



This figure is a scatter plot for the two variables CVSize and Expectation.

A positive correlation implies that larger variation in historical revenues is associated with higher expectations of future revenues

With the conclusion that smaller firms were expecting revenues to increase more, the next step was to further analyze the real outcomes to determine the performance of their forecasts. As already mentioned in the *Empirical Findings*, forecasts were generally optimistically biased independent on firm size. Moreover, as evident by the above, small firms expected themselves to produce higher revenues. Conducting correlation tests indicated significant relationship - where smaller firms exhibited a higher degree of optimistic bias (p-value=0,05), see Table 13. Consequently, small firms expected to grow but were not able to reach their forecasted revenues. Thus, it is fundamental to emphasize that medium and large firms were still optimistic, yet small companies demonstrated optimistically biased to a larger extent. Table 12 demonstrates the average degree of optimism from origin of the size classification.

TABLE 12. Descriptive statistics for size classification

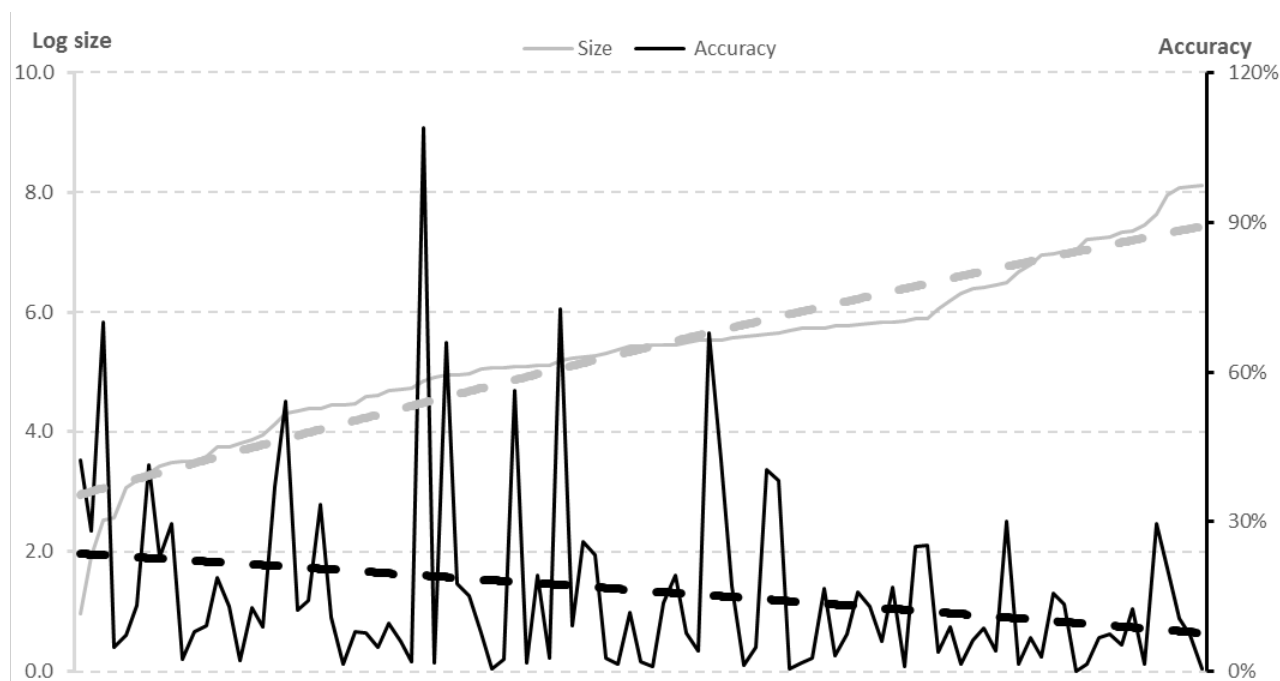
	Bias			Accuracy			Expectation		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Min	-28%	-19%	-30%	1%	0%	0%	-1%	-8%	-10%
Mean	14%	12%	3%	19%	17%	9%	31%	19%	8%
Median	11%	3%	2%	13%	9%	7%	31%	14%	8%
Max	70%	109%	30%	70%	109%	30%	84%	95%	39%
SD	22%	26%	12%	17%	23%	8%	25%	21%	10%
Skewness	67%	178%	-31%	139%	222%	132%	48%	182%	83%

This table presents descriptive data about the three categories of firms as measured by size.

Even though no hypothesis had been developed with regard to bias and volatility in revenues, companies with high revenue volatility were found to exhibit a higher degree of optimistic bias compared to those with more stable historical revenues. This is partly in line with findings of Lim (2001), who found forecast bias within small firms tended to be optimistic when their revenues were volatile.

In line with expectations, forecast accuracy was found to be associated with firm size. Figure 19 demonstrates the relationship between average accuracy for the first two years after the transaction and the size. The figure indicates the development of accuracy and size for every transaction. A value close to zero indicates a well-estimated forecast with good accuracy close to outcome. Following the trend line shows that forecast accuracy was associated with firm size, as the accuracy was better for larger firms. As expected, small companies revealed both higher optimistic forecasts and worse accuracy compared to the rest of the sample.

FIGURE 19. Size and accuracy



The figure represent all the transactions ordered by size and their corresponding accuracy.

Note that size is measured by the logarithm of the mean revenue for the three prior years of the transaction

Contradictory to Hsu, Hay & Weil (2000) and Brown, Hillegeist & Lo (2005) who found that larger companies were pessimistic when issuing forecasts, the opposite results were found in this study.

TABLE 13. Pearson correlation tests for size and coefficient of variation in size

	<u>Bias</u>	<u>Accuracy</u>	<u>Expectation</u>
<u>Size</u>			
R ²	0.04	0.06	0.25
Coefficient	-0.07	-0.22	-0.17
p-value	0.05	0.01*	0.00*
<u>CV Size</u>			
R ²	0.04	0.02	0.42
Coefficient	0.22	0.36	0.68
p-value	0.04*	0.20	0.00*

Note that the significant results are highlighted by the asterisk next to the p-value

Hypothesis one can be confirmed. Especially that forecasts issued by smaller firms are characterized by a higher degree of optimistic bias compared to medium and large firms when being subject to an M&A. Yet, medium and large firms were still producing optimistic forecasts as Table 12 demonstrates. Thus, their forecast performance was still better compared to smaller firms, meaning less optimistic bias and better accuracy. It is obvious that firm size is a factor to consider when analyzing forecast performance and that it differs across firms. The following hypothesis was confirmed:

H1. Smaller firms will issue more optimistic revenue forecasts and consequently higher optimistic forecast bias when subject to a potential M&A.

(2) Financial condition

It is evident that companies subject to a potential M&A issued optimistic forecast bias and the extent of bias differed for different firm sizes. Building on the existence of bias made it interesting to analyze if the degree of optimism differed for financially distressed firms compared to non-distressed. This was also stated in the hypothesis developed.

As stated in the *Empirical Findings*, financial condition can be measured using several different approaches. Yet, using only one metric limit the objectivity of the current state of financial condition, seeing how one metric cannot capture all the variables shaping the financial condition of a firm. Therefore, following Ota (2006) results of a relationship between higher debt ratio and financial distress, this report used debt ratio combined with the widely used net debt and O-score to form a comprehensive package, encapsulating a wide range of variables. Net debt and debt ratio contributed with different approaches to calculate financial risk, while Ohlsons O-score was slightly different as it considered the probability of going bankrupt within two years.

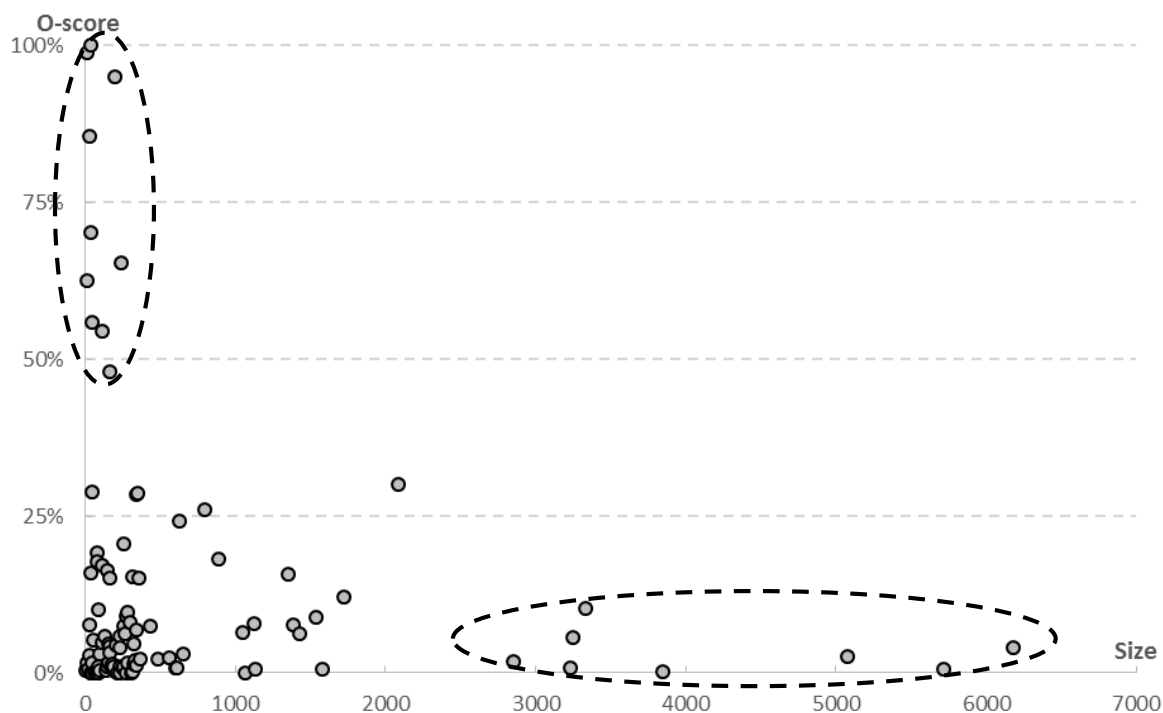
To identify how the degree of optimism differed in each of the three measures of financial condition, they have all been analyzed independently in separate t-tests and analyzed in relation to expectation, bias and accuracy. Consequently nine values were calculated to identify the associations among the different variables. Further attention was given to firms demonstrating financial distress. Table 14, shows the results from the t-test for each variable. The forecast performance could not be associated with financial distress for any analyzed variable. Unexpectedly, an uncertain relationship between net debt and accuracy was discovered, indicating that higher net debt was associated with more accurate forecasts (p-value=0,08). A plausible explanation for this finding could be that firms with high net debt

have a more stable environment to forecast in leading to higher accuracy. The argument is that they would not have been “allowed” to take interest bearing bank loans had they shown high historical volatility.

TABLE 14. T-tests for financial condition

	<u>Expectation</u>	<u>Bias</u>	<u>Accuracy</u>
<u>Debt ratio</u>			
R ²	0.01	0.01	0.01
Coefficient	-0.01	0.00	-0.02
p-value	0.31	0.48	0.25
<u>Net debt</u>			
R ²	0.04	0.01	0.03
Coefficient	-0.02	-0.01	-0.03
p-value	0.04*	0.47	0.08
<u>O-score</u>			
R ²	0.04	0.00	0.00
Coefficient	0.02	0.00	0.01
p-value	0.04*	0.65	0.54

FIGURE 20. O-score and size



The scatterplot above demonstrates the association between O-score and size.

The inverse relationship implies that the most financially distressed firms are also among the smallest

The only significant relationship found was between net debt ($p\text{-value}=0,04$), O-score ($p\text{-value}=0,04$) and expectation, indicating that increasing net debt is associated with lower expectations on increasing revenues.

Further, net debt and debt ratio was not associated with forecast performance with any significance. Looking at the circles in Figure 20 above shows that small firms are displaying a high probability of bankruptcy compared to large firms when comparing the probability to the average revenue three years prior to transaction. This may imply that although small firms were found to be more optimistic, it could not be assumed to be so because of their financial condition.

There can be several explanations for why no significance to forecast performance was found. The quality of input data varied especially for net debt. Firstly, many financial statements did not include cash or equivalent. This was rather unexpected, since cash was perceived as a financial safety. However, lacking knowledge about individual accounting principles made it hard to interpret the reason for this result. Secondly, information about the financial debt was mostly inadequate and interest-bearing liabilities were typically not expressed very well. It was also discovered that interest expenditures existed, although interest-bearing liabilities were not presented. The reason for this can of course be that amortization has been made during the fiscal year, yet no amortization charges were found in the financing cash flow. Undoubtedly, this affected the quality of the data when comparing net debt to financial conditions.

Shifting the focus towards debt ratio and O-score, these were relatively straightforward to calculate given that input data was readily obtained from the financial statements without any ambiguity. The transparency and consequently precision of these numbers were therefore superior compared to net debt. However, it should also be pointed out that estimating financial risk through debt ratio can be rather subjective as it only accounts for the association between two factors (total liabilities and equity). In addition, the analyzed sample is relatively small compared to earlier research in the same field. As a result, an absence of financial distressed firms or lack of differentiation could be a reason for the lack of significance, although this seemed not to be the case (see Figure 11).

Another reasons for the absence of significant associations could be that managers during M&A did not have similar incentives as Koch (1999) found evidence of - that financially distressed managers had more incentives and were more resistant to consider potential penalties due to the fact that their firm or position may cease to exist. Managers issuing

forecasts during M&A were probably not apprehensive about the survival of their firms, given that the purpose was reasonably different than going bankrupt and operations would be preserved after the transaction would have been completed. This could explain why financial distressed firms did not show higher degree of optimism compared to the rest of the sample.

In conclusion, optimistic bias and worse accuracy prevailed in the majority of the transactions, however no certain association could be found between financial distress and forecast performance. This basically implied that financially distressed firms did not demonstrate any larger degree of optimism compared to non-distressed firms. Thus, the following hypothesis is not confirmed:

H2. Firms in poor financial condition will issue more optimistic forecasts and consequently higher optimistic forecast bias when subject to a potential M&A.

(3) Industry

It was argued earlier that the nature of the industry would incline actors to forecast differently on the basis of different demand, growth, volatility, heterogeneity, concentration, competition and more. There were two general arguments outlined here. One was that more complex and volatile industries would pose a more difficult forecasting effort and result in worse accuracy and more optimistic bias. The other argument originated from incentives, supposedly a result of a conscious action to influence stakeholders. The hypothesis was then developed to incorporate these factors. In reality, testing them all thoroughly is beyond the scope of this report. Rather, the analysis is carried out by testing the expectation, bias and accuracy across the five aggregated industry groups: 1) *Industrial* 2) *Retail* 3) *Services* 4) *Public services* and 5) *Other*. The “other” category is hard to assess and is only included for completeness. The differences between the groups were made on the basis of different core business activities. However, it is worth reiterating that each industry group is internally very heterogeneous which means that these above-mentioned industry factors may not have been clearly distinct. Furthermore, there is certainly some level over overlap, which undeniably would result in a less accurate analysis.

The analysis used one-way ANOVA and Mood’s median tests to assess differences between groups. The former tests the mean and entail stronger adherence to normality assumptions. Since those assumptions were weak at best and the sample had a strong variance, the Moods median may have had allowed for better comparison. Although using both allowed better insight into differences in the groups. The main benefit of using these multi sample

comparisons was to directly tell whether any differences between the groups were statistically significant. If that did not prove to be the case, then any further analysis on the specific variable would have been futile. Carrying out several t-tests for each industry would increase the probability of making a type 1 error since each test would be carried out on the same sample, which again speaks in favor the more cautious approach used here. However, using both ANOVA and Moods mean also increased the risk for type 1 errors for the same reason. Following the structure in the previous section, expectation, bias and accuracy were tested separately in that order and previous research were then introduced to compare and contrast the findings.

Table 15 shows the result of the one-way ANOVA test and Moods median test on the expectation, bias and accuracy. The significant p-value indicated that at least one group is statistically significantly different from the rest. Which one that was required further testing. The numbers revealed that the industry group *services* had a higher average expectation than the other three, and thus entailed looking further into. The median expectation in each group informed us that *services* and *public services* had conceivable deviations from the sample as a whole, and thus also necessitated further analysis.

TABLE 15. Multicategorical tests for industry groups

	<u>Industrial</u>	<u>Retail</u>	<u>Services</u>	<u>Public services</u>	<u>Other</u>	<u>p-value</u>
<u>Expectation</u>						
Mean	16%	15%	29%	13%	29%	0.07
Median	11%	14%	19%	10%	23%	0.03*
StD	21%	11%	24%	13%	27%	0.03*
<u>Bias</u>						
Mean	12%	9%	18%	6%	7%	0.49
Median	3%	7%	13%	2%	2%	0.51
StD	27%	15%	29%	9%	21%	0.11
<u>Accuracy</u>						
Mean	17%	12%	24%	8%	15%	0.19
Median	10%	8%	13%	4%	9%	0.61
StD	23%	12%	24%	7%	16%	0.40

The p-values are based one-way ANOVA, Moods median and Levenes test for the mean, median and variance respectively.

Five t-tests assuming unequal variances were made, one for each industry group with results shown in Table 16. All industry groups demonstrated p-values around 0,05-0,14. *Public services* seemed to be the most noteworthy one and the results indicated that this group had a lower average expectation than the rest. Next, additional Moods median tests were carried out for the five industry groups as well. Here, *services* and again *public services* seemed to differ. The results so far are inconclusive, but *public services* were clearly different and some indications of *services* having a higher expectation than the rest. As such, the findings suggested that schools and companies working with human health and social work activities were less optimistic about the future by forecasting more modest growth rates in general.

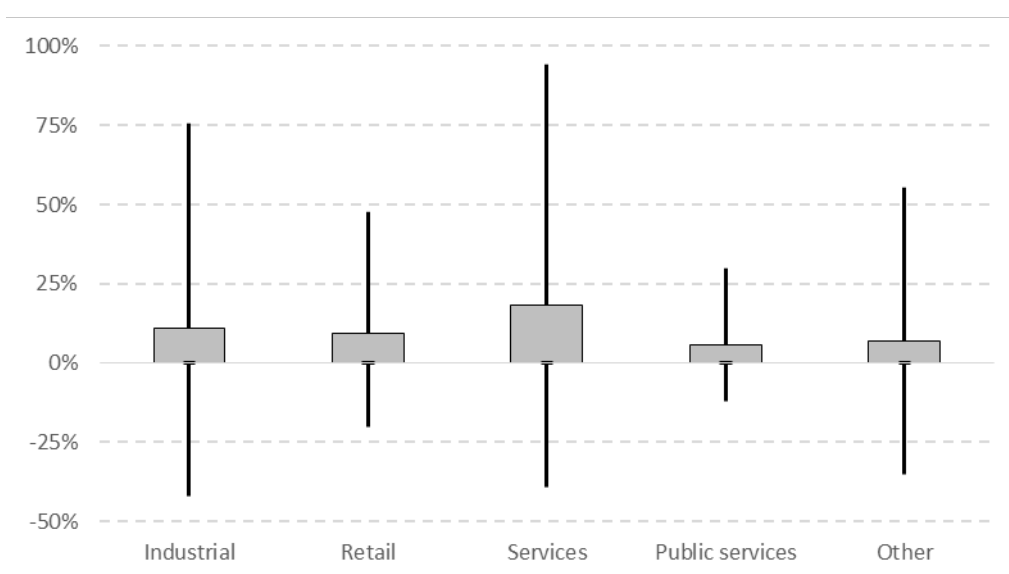
TABLE 16. Tests for individual industry groups for expectation

	<u>Industrial</u>	<u>Retail</u>	<u>Services</u>	<u>Public services</u>	<u>Other</u>
Mean Industry group	16%	15%	29%	13%	29%
Mean Compared sample	22%	21%	18%	21%	18%
p-value (T-test)	0.14	0.09	0.11	0.05	0.08
p-value (Mood's median)	0.38	0.80	0.06	0.04*	0.20

The table shows the results from T-tests and Mood's median on each industry group compared to the other four groups.

The results regarding bias displayed no significant differences among the industry groups. Looking more carefully at the numbers might indicate that *public services* were less biased, which would be an expected result given their more modest forecasts. In contrast, *services* appeared to have a higher average bias compared to the rest, again in line with what one would have expected given higher the expectation. The issue here is that there were considerable internal variations within each industry group. Figure 21 shows the average bias for each industry group and the two error bars expresses two standard deviations in either direction. The variance lowered the p-values. By carrying out a t-test on difference in mean between *public services* compared to the rest yielded a p-value of 6.2% which indicated a possible relationship. Nonetheless, since the initial multi-sample tests did not reveal any reason to continue testing, it would be better not to do any further analysis to avoid making unnecessary type 1 errors.

FIGURE 21. Bias for industry groups



The figure illustrates the mean and two standard deviations in either direction for each industry group

Finally, the equivalent analysis was carried out on the accuracy. In large, the same results were found for this variable with no significance to speak of albeit a small inclination to better forecasts performance for *public services* and worse forecast performance for *services*.

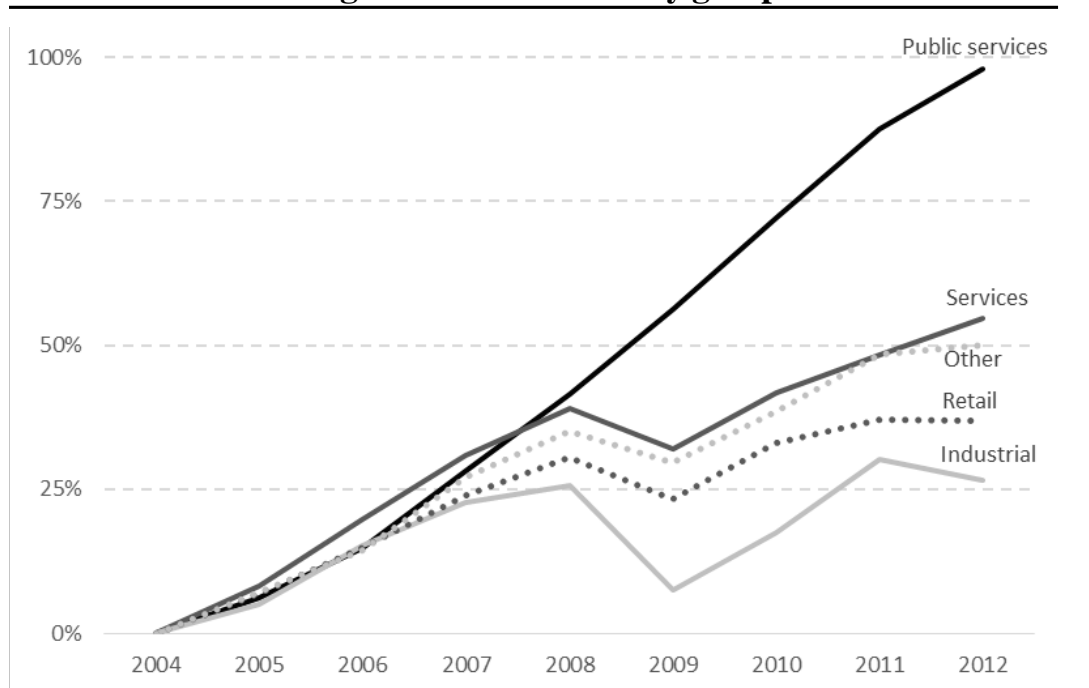
So what characterizes these two industry groups, *services* and *public services*? To recap, *public services* was composed of firms categorized as either schools or those working with human health and social work activities. Their customers and consequently demand functions can be assumed to differ quite a bit from regular firms. It was argued that the needs for these services are less dependent on market conditions than traditional businesses. In addition, the industry group differs in the regard that it have been subject to specific regulations. *Services* was made up of banks, insurance companies, consultants, architects, technical specialists and various administrative and support service activities. Needless to say, this group differed in having services as their core value proposition as opposed to products. In addition, their customers were mainly companies themselves, and as such they typically adhered to business-to-business operations. These customers were likely fewer in numbers but larger in size, which would have made the demand more sensitive to changes in demand and consequently less predictable.

Looking back at earlier research, it was mentioned that several scholars had found stable and tangible industries to be characterized by having less optimistic bias, and better accuracy. This followed the logic that such industries carried less uncertainty, and hence making it easier to forecast. The literature review also showed that some researchers had found market

concentration and competition as critical factors for assessing forecast performance. Their findings showed that higher market concentration and lower competition would cause more pessimistic bias. Higher concentration would imply higher profitability and thus incentivize larger actors to issue less optimistic forecast to discourage new entrants. Another argument was made where more concentrated industries would be more predisposed to litigation risks and thus forecast more modestly. Higher levels of competition would cause stronger pressure on maintaining proper forecasting processes and thus keep the accuracy better.

Using this as a theoretical ground, a comparison could be made by analyzing the industry groups in these regards. Figure 22 shows the development of each industry group over the analyzed period, measured as revenue percentages growth. Figure 23 also demonstrates some comparative average numbers for each industry, namely industry growth and market structure indicators. Starting with public services, the results found here partly support earlier findings as the *public services* have experienced much less growth variability than the other industries. Interestingly, the industry group had undergone a larger overall growth compared to the other groups as a result of a more stable period during the financial crisis as demonstrated in Figure 22. Clearly this supported the notion that dynamic market and business cycle fluctuations had less effect on this industry. In addition, the industry was fairly concentrated and had low rates of bankruptcy which would have indicated lower levels of competition and speak in favor of less optimistically biased revenues. However, it also had a numerous new entrants that may have been due to the deregulation initiatives, incentivizing new private startups, particularly in the health service area. Generally, the numbers indicated that the industry should have had less optimism and better accuracy, which seemed to align with the findings.

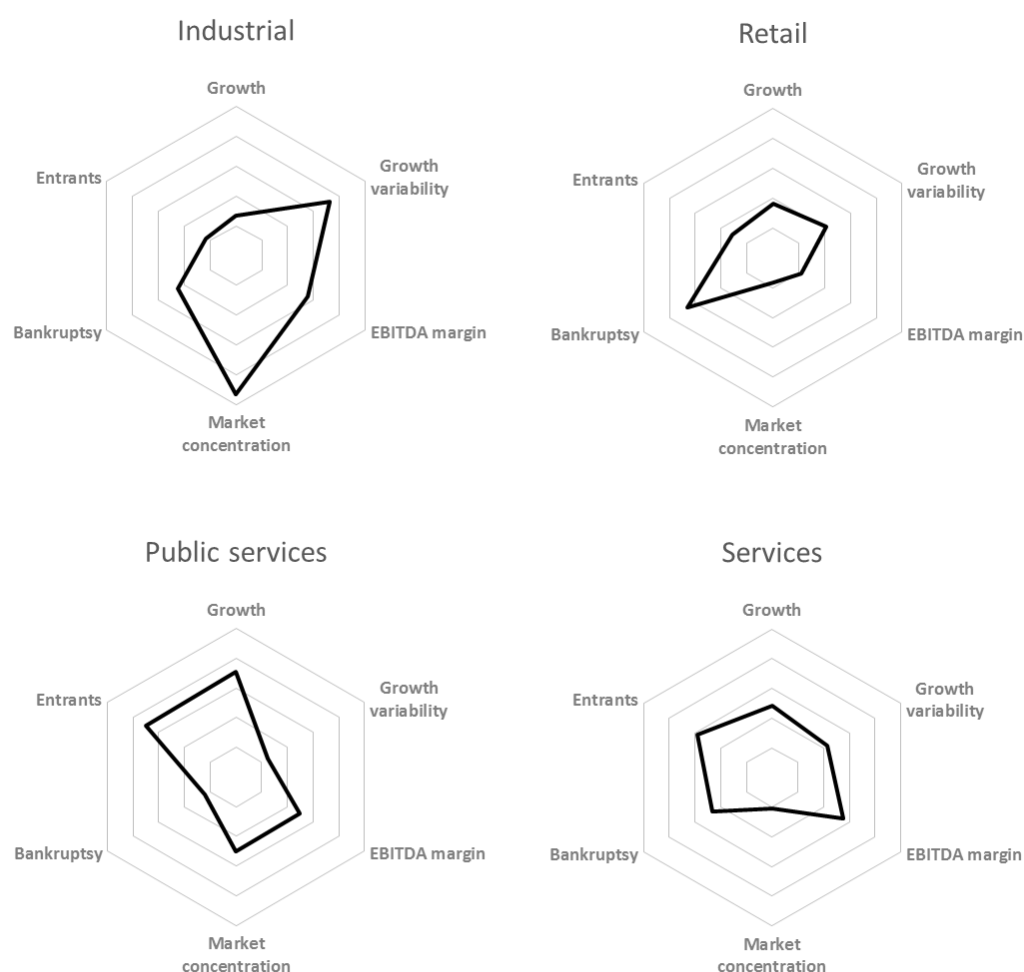
FIGURE 22. Revenue growth across industry groups



The time series measures the aggregated annual growth over each industry group in terms of revenues for Swedish firms
The calculations are based on data from Statistics Sweden

Looking at *services*, this industry had experienced a fairly strong growth during the analyzed period, and with reasonably high variability. It was also much less concentrated than the former and with a decent number of new entrants and average bankruptcy rates. The Figure 23 below suggests a somewhat higher optimism than the other industries, which again conformed to the results.

FIGURE 23. Comparative variables for industry groups



The *Growth* is measured as the average percentage growth across the time period

The *Growth variability* variable is measured as the average standard deviation of the percentage change between every year.

The *EBITDA margin* is measured by taking the total EBITDA within each industry divided by the total revenue in the same industry and average over the years

The *Market concentration* is measured as the proportion of large companies (>500 employees) to the total number of companies in each industry group and averaged over the years

The *Bankruptcy* is measured as the average percentage of bankruptcies for every year

The *Entrants* is measured as the average percentage new companies for every year

All measures are then compared relatively to the other four e.g. the sum of the growth variable in each industry group adds up to 100%

In spite of the arguments outlined here, the hypothesis H2 cannot be confirmed on the basis of lacking statistical significance. However, the expectation were significantly different and were seemingly in line with the expectations based on previous research. In consequence, it would be unwise to completely disregard the industry factor when assessing forecast performance in M&A. The specific cause of the difference in expectation is much less obvious. It would seem unlikely that the psychology of individuals would differ drastically between different industries (although some might argue different personalities are drawn to different business activities). In that sense, incentives are more the probable cause here. However, a more direct and simple answer would tell us that it is not incentives but instead

the complexity and uncertainty in the industry that would be the cause. In other words, more seemingly random market developments are just harder to forecast with worse forecasting performance as a natural result. To conclude, the following hypothesis cannot be confirmed with statistical significance:

H3. Firms in volatile, fast growing, less competitive and fragmented industries will issue more optimistic revenue forecasts and consequently higher optimistic forecast bias when subject to a potential M&A.

(4) Business cycle

As pointed out earlier, the hypothesis behind the business cycle factor was that optimism would be expected when the national economy was at its strongest, during the peak of the business cycle right before a forthcoming downturn. Conversely, pessimism (or less optimism) would be expected in the trough of the business cycle. This would be a result from the general concurrent mood that were pervading the society and directly, or indirectly, affect the outcome of forecasting as well. Several researchers had found this to be the case, particularly when observing forecasts issued by analysts of various kinds. What researchers have not generally analyzed was whether the effect was also prevalent when comparing macro management forecasts to macro forecasts issued by different agencies and banks. These forecasts were presumed to be an indicator of the general expectations of the economic development. Thus, one can ask: If the current state of the economy carries weight in management forecasts, can the same be said for expected future development of the economy? Moreover, by analyzing the bias and accuracy of these macro forecasts and placing them in relation to the management forecasts, it can be reasoned to what degree the errors are deriving from external factors versus internal factors.

For these reasons, the analysis in this section measured associations between the GDP outcome, GDP expectation and GDP forecasts errors to the expectation, bias and accuracy of the managers. There are at least two ways to go about this. First is by measuring over all 103 transactions. Another approach would be to categorize transactions into their respective year and measure correlation to the corresponding GDP and average value of the management forecasts for the same year. The former would more accurately display the potential effect of the GDP on the individual forecasts while the latter would serve the benefit of measuring equal time horizons and ignore variations between individual transactions. Both approaches

were used. The GDP expectation was measured as the average over the first two years, issued one quarter prior to the transaction year.

Table 17 shows the results from the test on the expectation, bias and accuracy. Noticeable when looking at the expectation is that the only tests that presented a significant correlation ($p < 0,05$) were the GDP outcome and GDP expectation when measuring the average between years. Corresponding Figure 24 and Figure 25 illustrates these variables. The significance GDP outcome suggested that the current state of the economy did influence managers by causing them to forecast higher during upturns and vice versa. The compared expectation of both also displayed significance and aligned well over the period 2005-2011 signifying one or two things: Firstly, the future outlook could have been similar for forecasters of the macro environments and managers based on some unobserved third variable that both actors were influenced by. Secondly, one of them may have been influenced by the other and have incorporated this piece of information into their own forecasts. Since the GDP forecasts, measured here, were those of one quarter *prior* to the issue of the forecast for the firm, the causal relationship can only be one sided, if there is one to begin with. That is, managers could have looked to the GDP forecasts (or equivalent correlated measure of economic development) for information about macro developments and have taken these into account. However, interestingly when analyzing the correlation between each individual forecast to the GDP values, the relationship seemed to disappear. This is likely the result from the large internal differences in each year, a possible result from a relative small sample of forecasts. It shows that both measures are necessary to capture the full picture.

TABLE 17. Pearson correlation tests for GDP measures

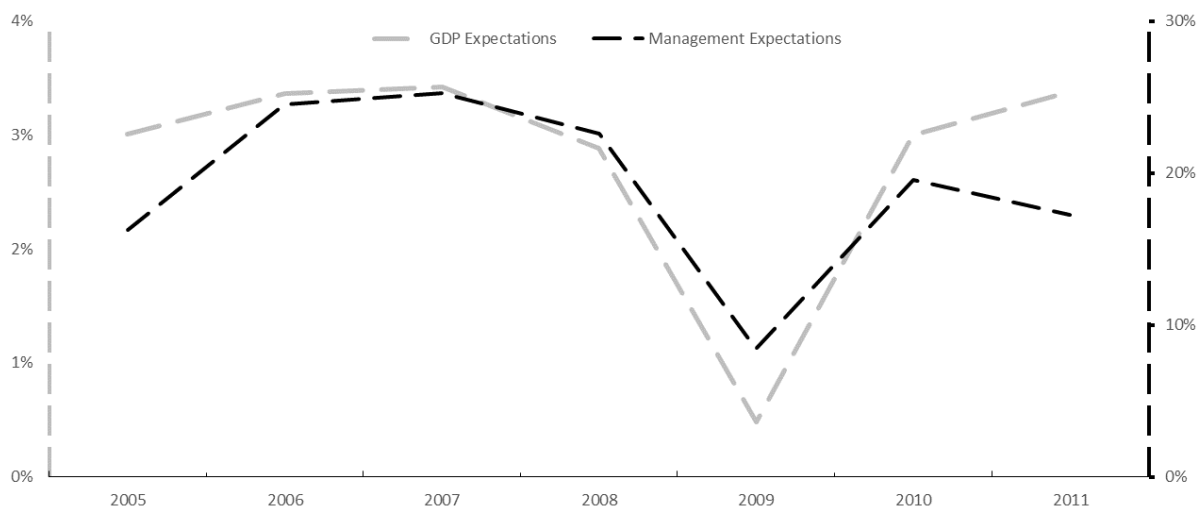
	Expectation		Bias		Accuracy	
	Ind	Agg	Ind	Agg	Ind	Agg
GDP outcome						
R ²	0.00	0.37	0.00	0.01	0.01	0.02
Coefficient	0.00	0.05	0.00	0.00	-0.01	0.00
p-value	0.97	0.00*	0.86	0.55	0.45	0.49
GDP Forecast						
R ²	0.01	0.69	0.00	0.27	0.00	0.03
Coefficient	0.01	0.05	0.01	0.03	-0.01	0.02
p-value	0.38	0.02*	0.74	0.23	0.81	0.71
GDP Bias						
R ²	0.00	0.08	0.03	0.64	0.01	0.36
Coefficient	0.00	0.01	0.02	0.02	0.04	0.03
p-value	0.67	0.54	0.08	0.03*	0.22	0.15

Ind refers to measures over every transaction while Agg refers to measures for tests over aggregated years.

The first measures thus considers variance within each year group and will logically display less p-values as a result of this

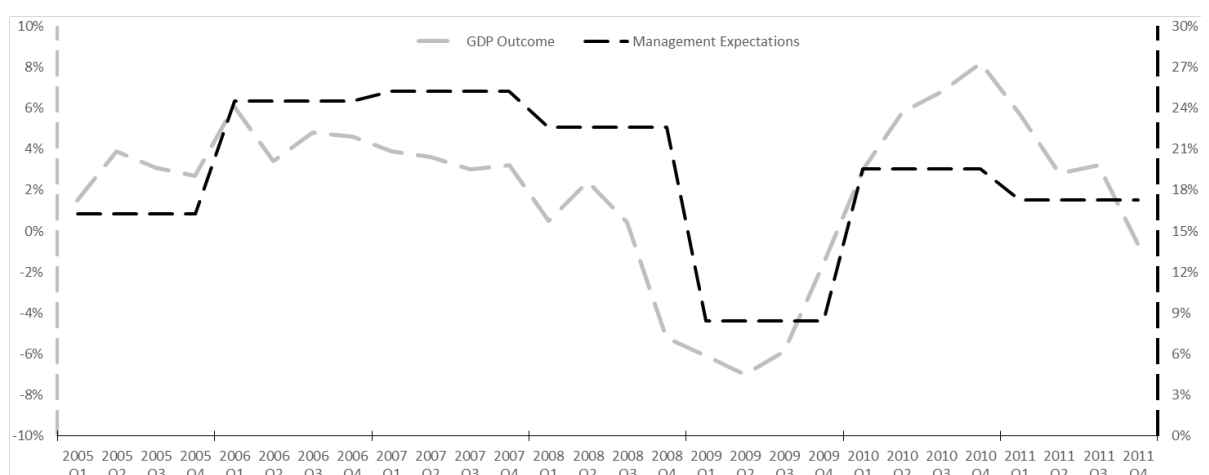
GDP Bias is taken at absolute values when measured to accuracy

FIGURE 24. Management expectations and GDP expectations



This figure displays the forecasts of managers and macro economists over the analyzed years.

FIGURE 25. Management expectations and GDP quarterly outcome

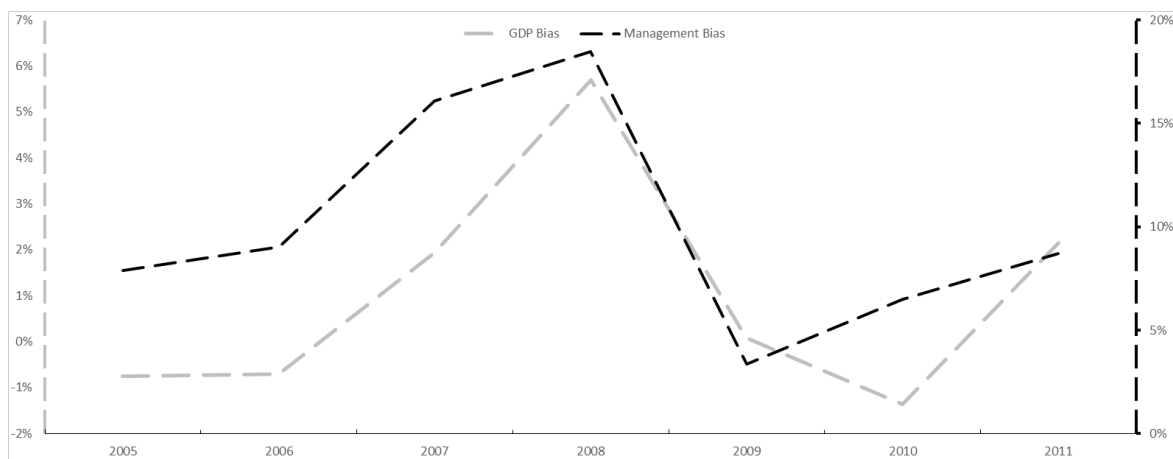


This figure displays the expectations of managers with the contemporary GDP values.

Note that the two y-axes starts at -10% and 0% respectively.

When observing the results for the bias, a similar picture revealed itself in that the association was weakened through the comparison of individual transactions compared to the average for each year. Yet, there was a strong positive correlation in the bias between the forecasts in both cases. Figure 26 illustrates these results below. To reiterate, the bias here was measured as the average bias for the two subsequent year of each respective forecast, issued at a similar time. This correlation implied that similar overestimation and underestimations were prevalent during the business cycle. A key insight then was that the underlying incentives or cognitive biases were not necessary unique to managers, or equivalently that macro forecasters and managers faced at least one similar incitement or cognitive bias. Since the managers' forecasts here were argued to have "extra" incentives to overestimate their revenues for business reasons, a more likely common underlying source of bias would have been cognitive biases. The results also shows that bias was not significantly correlated to the contemporary GDP levels or GDP expectation.

FIGURE 26. Management forecast bias and GDP bias



This figure displays the bias of managers and macro forecasters.

Note that the two y-axes starts at -2% and 0% respectively.

Finally, similar test results were carried out for the accuracy with the exception that the GDP errors were taken at their absolute value to ensure accuracy was compared with accuracy. No significance was found between the variables in any tests carried out here. This would imply that the economic environment at large could not explain accuracy. Intuitively, It was expected that the accuracy to be lower for managers as well as macro forecasters when the economy was in quick growth or decline, but this could not be verified.

In general, the positive coefficients found throughout this section suggested that the economy at large was not independent of managers' expectations for the future. The GDP outcome indicated that the current state of the economy did influence the future expectations by implying a higher percentage revenue growth in years to come. However, given the non-significance of the bias and accuracy, these expectations may not have been justified. The GDP forecasts also showed some associations, but not generally strong enough to say for sure, given the sample size. Furthermore, when looking more careful at the calculations carried out in this section, the associations seemed to be strongest during the fluctuating years of the financial crisis. This would have supported most of the earlier findings that emphasized strong optimistic bias right before a downturn and a pessimistic bias right before an upturn. Nonetheless, in average, the errors stayed positive throughout the period indicating that optimistic bias was prevalent even during the trough of the economic downturn, standing in contrast to earlier findings where pessimism was found more prevalent during certain periods of the business cycle. This could imply that the nature of an M&A may prompts stronger optimism. The closest earlier research in terms of management forecasts were Hsu, Hay and Weil (2000) who compared forecasts right before IPO prospectures. This scenario arguably

carries similar incentives to forecast optimistically which is to please shareholders. Their finding that the specific year of 1987 was correlated with significant stronger optimistic bias aligns well with the findings here, since that year was just before a downturn. Overall though, their findings did not have the similar degree of optimistic bias throughout their analyzed period. As such, the consistent optimistic bias found here may have indicated that the hypothesized incentives during M&A exist. Also important to highlight was the small amount of transaction analyzed for year 2009. These may have had an impact on the comparison between macro forecasts and those issued by managers.

Returning to the hypothesis mentioned at the outset, one can without hesitation confirm that the macro economy influenced managers in their revenue forecasts. The bias of macro forecasters followed those of managers well over the business cycle which proposed comparable future expectations and outcome for both actors. The bias was also shown to be at its highest in the year 2008 and lowest in 2009 in line with the expectations of the turning points of the business cycle. Combining these findings weakly confirm the hypothesis that managers' bias can be partly explained by the business cycle.

H4. Firms will issue more optimistic revenue forecasts and consequently higher optimistic forecast bias during the peak of the business cycle when subject to a potential M&A.

6. Conclusions

The purpose of this study was to determine forecast expectation and performance by the degree of bias and accuracy in revenue forecasts issued during M&A with regard to (1) *firm size*, (2) *financial condition*, (3) *industry* and (4) *business cycle*. The overall case was made that all firms being subject to M&A will demonstrate optimistic bias on the basis of strong financial incentives for the forecaster. On top of this, it was hypothesized that more optimistic bias would be identified for (1) smaller firms, (2) financially distressed firms, (3) firms in dynamic, fast growing, less competitive and fragmented industries and (4) during the peak of a business cycle. The findings resulted in a strong confirmation of (1), weak confirmation of (4) and failures to confirm (2) and (3) with statistical significance.

The average forecasted revenue growth between two years i.e. the expectation was observed to be 20 percent over a three year period. The forecast performance was calculated using measures of bias and accuracy, which was found to be 17 percent and 23 percent respectively over the same three years. Similarly, 94 percent of the sample expected growth. Yet, only 68 percent managed to grow after the potential transaction resulting in optimistic bias in 67 of 103 firms. However, expectation, bias and accuracy displayed large variations with standard deviations around 20-30 percent. In addition less accurate and more optimistic forecasts was observed as the forecast horizon lengthened. The degree of bias found was in line with the findings of Stunda (1996; 2000) who identified optimistic bias at 21 percent and 19 percent during M&A and non-normal activities respectively.

Findings confirmed the existence of optimistic bias across all firm sizes. Especially those forecasts issued by smaller firms were characterized by a significantly higher degree of optimistic bias compared to medium and large firms. This further followed that forecast accuracy was associated with firm size, since the accuracy was worse for smaller companies. Accordingly, medium and large firms demonstrate less optimism and consequently more accurate forecasts. In addition, it was verified that firms with stronger variation in revenues exhibited higher optimism, worse accuracy and higher expectations in general.

The majority of firms across all industry groups expected growth. Yet, it was found that firms within *public service* forecasted more moderate growth compared to the other industry groups. On the other end of the spectrum, the industry group *services* was found to estimate higher revenues. These behaviors consequently suggested a higher degree of optimistic bias

for *services* and a lower degree for *public service* firms, but was not confirmed on the basis of lacking statistical significance. The analysis on accuracy showed similar results as for bias for *public services* and *services*. No further significance was found in the other industries.

Financially distressed firms were not found to demonstrate any larger degree of optimistic bias, yet smaller firms were found to be more financially distressed. Surprisingly, a negative relationship was found between net debt and expectation, implying decreasing net debt to be associated with higher expectations on increasing revenues. In contrast, a positive significance was found between O-score and expectation, basically indicating that an increased probability of going bankrupt is associated with higher expectations on increasing revenues. No significant evidence was found between forecast performance and financial distress.

Finally, the current macro-economic condition was found to reflect managerial forecasts. A significant correlation was found between the yearly average managerial forecast to the yearly average GDP outcome and GDP forecasts. This suggests that both the current as well as future expectations of the macro economic development influences managers by causing them to forecast more aggressively in up turns and vice versa. However, due to the large variations between individual transactions the overall significance is weak at best. The prevalence of optimistic bias in macro-economic forecasts also reflected forecast issued by firms. This correlation implies that similar overestimations and underestimations are prevalent during a business cycle. No association to accuracy was found.

This study has contributed to research with additional evidence about forecast performance and behavior for firms in M&A. Seeing how findings in M&A is relatively unexplored, the results are important for the enhanced understanding about the level of bias and accuracy in this particular context, as it provides new support regarding the determinants above. The findings also facilitates further understanding in a larger context for the buyers and sellers being part of M&A since forecast performance can be better predicted given the identification of significant determinants. A more cautious approach can be taken by stakeholders when evaluating forecasts issued by firms where forecast performance tend to be less accurate, which can also provide additional insight when valuing the target company. This enhanced value will probably be indirectly provided to clients by supporting actors such as audit firms by taking a more prudent business evaluation towards firms where the forecast performance has been found to divert more strongly. Ultimately, these findings may help the buying firm to place a fairer bid for the target company and reduce some of the uncertainties involved in the transaction.

Further research

A natural extension to this research would be to further investigate forecasts in M&A using different determinants through the usage of the same data. As previous research has already pointed out, several determinants can be applied to determine forecast performance. The sample size of this thesis was rather small meaning that an increased number of forecasts would be preferable both to increase the likelihood of finding significant relationships to ensure deeper insight into forecast behavior and to facilitate finer discrimination among variables, in particular among industries. It may also be insightful to conduct multiple regression analysis to evaluate potential dependence and interactions of the independent variables in order to understand how and if they collectively contribute to forecast performance. Building on this, an in-sample sample regression model could be applied to out-of sample data to verify the predictive strength of the determinants found in this study. This is beneficial to strengthen the validity of the determinants and to quantify the actual impact in a real life application when working with business forecasts.

Since prior research has mainly focused on explaining different determinants in which forecast performance differs, shifting the focus towards processes in which forecasts are created may be an interesting area to investigate. As of now, the means to quantify cognitive biases and incentives are few and difficult without deeper insight into the forecasting process. It is then natural to shift focus towards this area. Relating this to this thesis would be a focus on the M&A process and in particular prior to the due diligence when the forecast is created. Whatever is causing the bias ought to be more easily identified by being aware of particulars of the forecasting process. Examples include a better understanding of what data and assumptions that are used in the forecast, whether it is a work of a single individual or a group and the expectations of the present M&A transaction.

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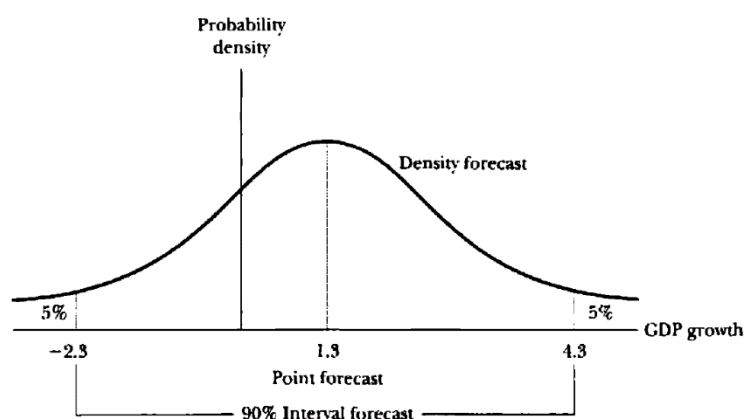
8. Appendix

Appendix A – Financial forecasting

Components of a forecast

The main components of a financial forecast consist of revenues, costs and profit. It has a specified forecast horizon and is generally forecasted in interval of days/weeks/months or years. For these reasons financial forecasts are represented as time series, as opposed to event outcome forecasts or event timing forecasts that forecasts a specific object (Diebold, 2006). Moreover, a forecast can be a *point forecast* which estimates single values, an *interval forecast* that uses prediction intervals to estimate a range outcomes accompanied with a specified probability, or a *density forecast* where the complete probability distribution is given at every point in time (Diebold, 2006). See the figure below of an illustration of these types. As it turns out, the most simple but least informative forecast, the point forecast is the most widely used, followed by interval forecasts which in turn is followed by density forecasts. It is no surprise given the ease of interpretation and construction compared to the other types (Diebold, 2006)

FIGURE 3.5
U.S. Real GDP
Growth: Point,
Interval, and
Density Forecasts



Point forecast, interval forecast and density forecast (Diebold, 2006)

Forecasting methods

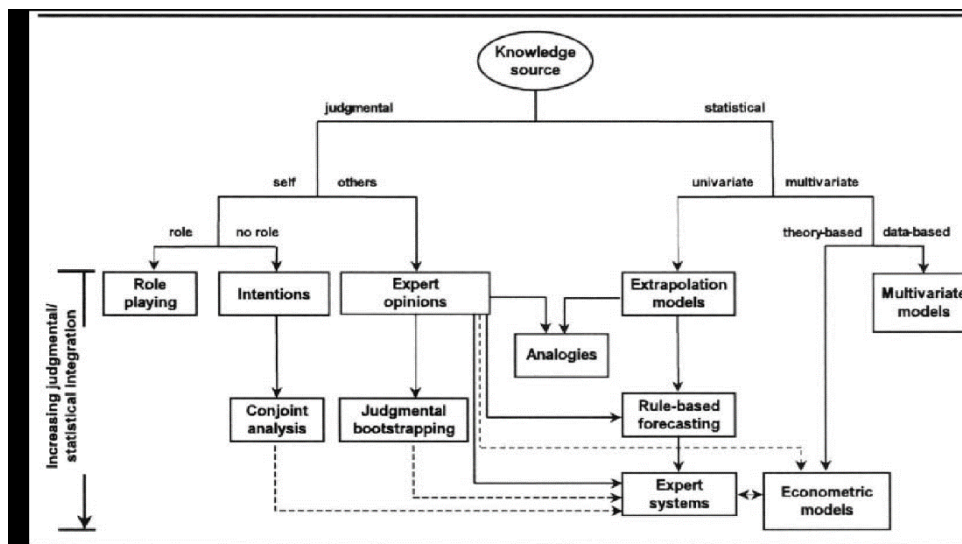
Proper forecasting process is argued to increase the opportunity to understand the dynamics of markets, customer behavior and simultaneously decrease the uncertainty provided to the companies' functions due to more accurate information. This facilitates better preparation for unexpected events and how to cope with them (Morlidge & Player, 2010). By understanding

and predicting forecast bias, it is possible to enhance the accuracy (Shaffer, 2003; Gilliland, 2010) through ex-post evaluation and adjustments to counteract for these effects. And by understanding the forecasting process, this may be possible. Consequently, if processes were associated with accuracy and bias in forecasts, then it would be reasonable to investigate it as such. However, for practical reasons most researchers evaluate forecasts and generalize findings based on statistical analyzes.

Aside from the impacts of the forecasting process itself, there are multiple methods for forecasting that play an important part. On a general level, these are either qualitative (judgmental forecasting), quantitative or a combination of the two. Certain authors consider only the quantitative approaches (Diebold, 2006). Others see their uses dependent on the situation, for example Morlidge and Player (2012) recommends judgmental models in the two extreme cases where the forecast is either very easy and well understood or when it is too complex for a quantitative model to cope with. Regardless of the method chosen, it is usually recommended to follow the parsimonious principle, which states that simple models are preferable to complex models, everything else equal, to maintain interpretability and unbiasedness (Diebold, 2006). In fact, Gilliland (2010, p. prologue) takes it a step further by arguing that there may be an inverse relationship between the effort put into a forecast model and its accuracy.

"The more a forecast is touched, the more it tends to go awry. Each process step, each opportunity to adjust a forecast, is just one more chance for wishes and politics and personal agendas to contaminate what should be an unbiased best guess at what is really going to happen" (Gilliland, 2010, p. prologue)

When forecasting revenues, it comes down to decomposing it into relevant components such as individual markets, customers, prices, products etc. (Tennent & Friend, 2005). Hence, the common, but often criticized, method of forecasting using a fixed growth rate based on previous revenues may only be justified if the reasons for doing so is well understood (Wellings, 2010). This is crucial as it indicates that purely historical revenue data may not alone encapsulate all the information necessary to make an accurate forecast. In turn, this would imply that some forecasting methods relying solely on historical data is insufficient for these means. The choice of method is dependent on various factors. Jae (2012) mentions a few: cost of developing the model compared to gains of using it (1), complexity of relationships of the forecasted objects (2), forecast horizon (3), accuracy requirements (4) tolerance for errors (5) and data availability (6).



Methods in forecasting (Armstrong, 2001)

Following the division of methods by Armstrong, 2001, judgmental methods may be developed based on the expertise of others or by going directly to the source. The expertise of people such as executives in finance, administration, purchasing, while fast and easy, contains factors such as group think and insulation that may limit objectivity and negatively influence the forecast accuracy. Although, consulting with the sales-force is believed to be beneficial due to their closeness to the customers and overall understanding of the market. The Delphi method aims to eliminate these factors by only allowing forecasts to be made independently. This is done by allowing an external party to iteratively gather and update forecasts from the experts. (Jae, 2012) Instead of consulting with experts, the forecaster may directly ask the people about their intentions. For example, in the context of revenue forecasts, one approach is to directly address the customers through customer surveys. Alternatively, when the actions are dependent on the actions of others, role-playing and game theory can be used to predict outcomes. (Armstrong, 2001)

On the quantitative side of forecasting, the forecaster generally uses historical data of a times series to create more or less complicated mathematical models. The most simple is commonly referred to as *naïve methods* where simple rules based on historical data dictates the forecast e.g. the revenue of the next time period equals the revenue today. Another step in complexity is using moving averages. For each forecasted time period, the forecaster simply calculates the average based on the last X time periods. Exponential smoothing is similar, put places higher value on more recent time period (Jae, 2012). Diebold (2006) proceeds to explain a more thorough mathematical approach to forecasting based on decomposition the time series into its trend, seasonal variation and cycles. By employing statistical models such as

Auto Regression (AR) and Moving Average (MA) models, it is possible to create sophisticated mathematics models capturing the rich historical information value. The commonalities of these approaches are that they extrapolate on historical data and nothing else.

Another significant part of quantitative forecasting uses more variables than history as inputs and attempt to measure associations between variables. Most common may be a regression models measuring linear dependence between the forecasted object (dependent variable) and other independent variables. Regression models may involve multiple variables and is then referred to multivariate regression. (Jay, 2012).

Appendix B – Revenue accounting practices

This section describes how reported revenues are dependent on the accounting principle used at the time of creation. Managers have various incentives to adjust the numbers to represent a distorted version of the truth. However, even when intentions are right, different standards, assumptions and estimates used will impact the size of the reported revenues (Berman, Case & Knight, 2006). To ensure proper comparison of revenues over time and between firms it is necessary to adjust the revenues properly to account for differences in the reporting, so called normalizing adjustments. Hence, the main features of reporting revenues are explained below.

Ever growing complex business activities have led to new forms of revenues and to that, new standards and regulations regarding of how to report them. According to Bonham (2010) it has become haphazard. It is not uncommon for posts in the financial statement to be reported according to whatever is beneficial to the firm at the time of creating the report. For instance, a firm may wish to aggregate or report higher numbers to hope for positive markets reactions and enhanced stock value or lower numbers to have a cause for blaming specific prior management in the event of an M&A.

Revenues are by some argued to be the most common post to manipulate (Berman, Case and Knight, 2006) and could have severe consequences to the financial statement as a whole. The accounting practices on this side of the financial statement are sometimes called income management. Berman, Case and Knight (2006) describes an example of how a company significantly improved their revenues by increasing their sale price of cable boxes to customers and simultaneously reimbursing the same amount for using their product i.e. for marketing purposes. This allowed the company to report higher revenues even though the same transaction was being carried out in practice. As a result, the reported earnings increased significantly as the “marketing costs” were depreciated over time.

The authors point to how assumptions and estimates lead to biases in the statements. They argue that:

“The “sales” figure on a company’s top line always reflects the accountants’ judgments about when they should recognize revenue. And where there is judgment, there is room for dispute—not to say manipulation.”

In the context of an M&A, the revenue is among the most crucial factors to consider in the valuation. Allman (2010) confirms the importance of revenues by referring to the fact that when forecasting, other components in the financial statement are derived from the revenues.

As such, the assumptions made behind the revenue numbers need to be assessed carefully. (Allman, 2010)

One main problem with reporting revenues is that of timing (Robinson, 2012). For example, should it be reported when a contract is signed, when the product or service is delivered, when the invoice is sent out or when the bill is paid (Berman, Case & Knight, 2006)? According to the International Financial Reporting Standards (IFRS) that revenues should be realized after a numbers of conditions are satisfied (IAS 18: Revenue, 2004):

- The entity has transferred to the buyer the significant risks and rewards of ownership of the goods;
- The entity retains neither continuing managerial involvement to the degree usually associated with ownership nor effective control over the goods sold;
- The amount of revenue can be measured reliably;
- It is probable that the economic benefits associated with the transaction will flow to the entity; and
- The costs incurred or to be incurred in respect of the transaction can be measured reliably.

Consequently, it is only when underlying uncertainties are resolved and the economic benefit can reliably flow to the entity that revenue can be justifiably recognized (Bonham, 2010).

Bonham (2010) denotes this timing issue as revenue recognition and describes two main approaches used in practice, the critical event approach and the accretion approach. The first approach simply states that the revenues are to be recognized when the critical act or decision has been made. For example at the time of a sale or completion of a product. The latter approach recognizes revenues earlier in the production process. The author argues the relevance of this approach when dealing with continuous usages. Typical situations are services, rentals, long-term contracts etc. A different kind of timing issues occurs when two transactions are linked as one and thus needs to be reported as such, as may be the case of mobile phones and service contracts. In the case of reported revenues that were later proven incorrect, such uncollectable revenues are to be recorded as expenses rather than adjusted revenues (Bonham, 2010).

Apart from the timing issue, there may be uncertainties regarding what qualifies as revenues and its measurement. Again returning to the IFRS prescriptions, revenues includes (IAS 18: Revenue, 2004):

- The sale of goods;
- The rendering of services; and
- The use by others of entity assets yielding interest, royalties and dividends.

Such revenues should be reflecting the “fair value” which in general just equals the cash or cash equivalent. Granted, if the revenues are postponed these two may not match. The solution this is by discounting future receipts according to an imputed rate of interest, which is either (IAS 18: Revenue, 2004):

- The prevailing rate for a similar instrument of an issuer with a similar credit rating; or
- A rate of interest that discounts the nominal amount of the instrument to the current cash sales price of the goods or services.

Adjusting revenues

When adjusting the financial statement, it is usually called normalization adjustments. It refers to an effort to “*convert the reported accounting information to amounts that show the true economic performance, financial position, and cash flow of the company*”. (Mellen & Evans, 2010) The authors mentions the most common factors:

- Tax adjustments e.g. excess compensations.
- Adjustments in the basis for accounting e.g. depreciation methods.
- Adjustments for non-operating or non-occurring items e.g. personal assets and expenses reported on the company.
- Differences between assets market value and the carried amount in the company’s books.

Such factors play a larger role in smaller businesses and thus needs to be examined more closely. Koller, Goedhart and Wessels (2010) demonstrates how new accounting policies can inflate revenues considerably in the case of Apple iPhones. Following an old accounting rule, Apple was discounting their revenues over a 24 month-period due to continuous software upgrades. A newer accounting rule recognized revenues at the time of a sale. With the transition to this new rule, the revenues should artificially spike. Needless to say, it is fruitful if these changes are disclosed in the statements, however some companies do not document them completely, which distort the perceived performance (Koller, Goedhart & Wessels, 2010).

To reverse or counteract the effect of these various adjustments, one needs to make new adjustments in return. Such adjustments are necessary in practically all posts in the financial statements, but for revenues in particular. Mellen & Evans (2010) mention the following aspects:

- Non-recurring revenue or income items e.g. sale of asset, insurance proceeds, large sale to customer or gain from a property condemnation.
- Non-operation items from income e.g. Interests and dividends beyond transactional-level cash balances, non-relevant rental incomes.

These are to be removed from the analysis since they are not indicative of future prospecting results or possible to anticipate in foresight. However, with some non-recurring items, it is worth reflecting upon their “recurability”. A strike, for example, may be a one-time event but also possible ensue again in the future.

In M&A situations, additional complexities arise. When analyzing organic revenue growth, in order to create internal consistency over years, revenues needs to be adjusted by spreading the revenues over the surrounding years of the M&A. Otherwise, the numbers will indicate a spike in growth and give a false sense of organic growth. In addition, M&A may need adjustments in synergy effects, which could prove to be complex (Hitchner, 2006; Koller, Goedhart & Wessels 2010; Roberts, 2009). Roberts (2009) claims that buyers may often not recognize when synergies are prevalent and a justifiable adjustments is valuable. In addition to mentioning the non-recurring - and non-operation items, he also claims necessary adjustments are those reflecting economies of scale, such as salary expenses in administration.

Koller, Goedhart and Wessels (2010) discuss the issues of currency and gives an example of how changes in currencies embedded in the revenues gives a false view of revenue growth. Jae (2012) recommends checking the financial statement for a variety of factors that might indicate suspicious accounting practices. A large gap in revenues over years resulting in weak association is a prime factor. He notes that revenues are reported in the beginning of the year, as may be the case for membership fees, provision fees may be varied over the years significantly and future revenues could be reported prior to their realization.

Conclusively, the individual company will use unique accounting approaches that may differ in time, depending on current goals and management. Hence, adjustments need to be made on a case-by-case basis.

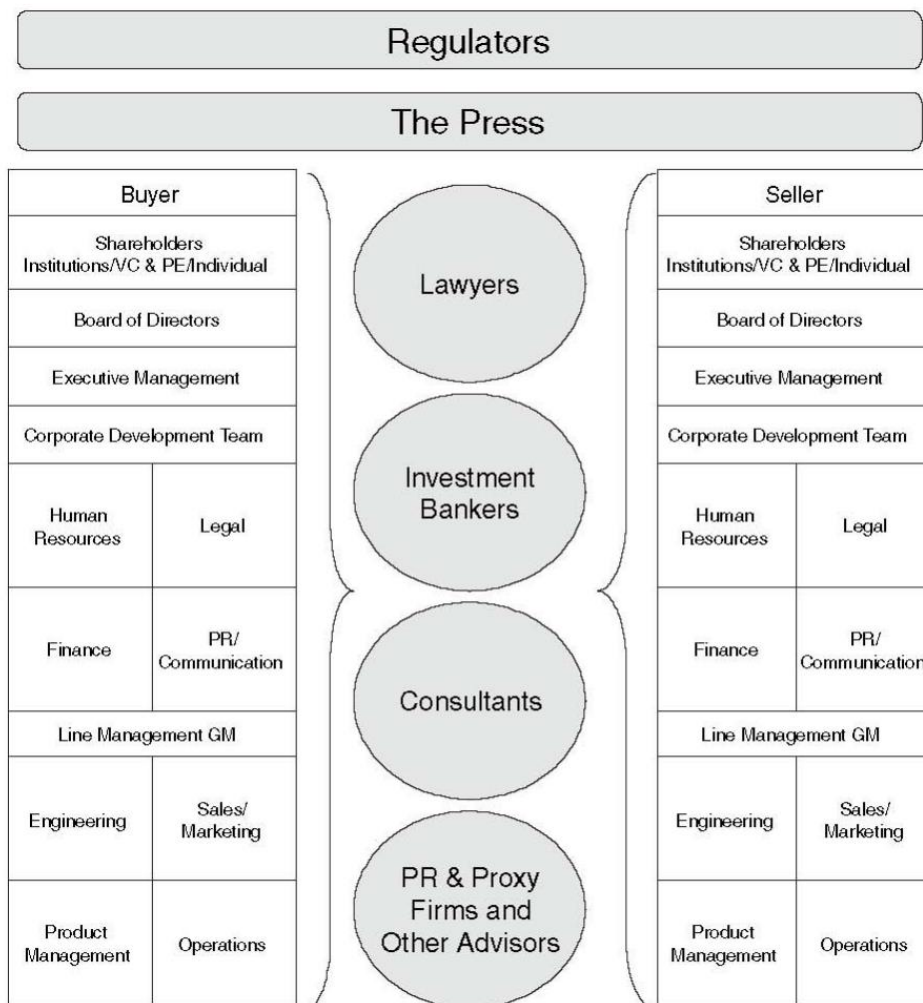
Appendix C – M&A

Strategies to grow and simultaneously deal with increased dynamics of markets are necessary in order to stay competitive. Inorganic growth through M&A have increased recently as industry growth rates stagnates, too many actors prevail in the marketplace or and the industry becomes fragmented (Jacob, 2006). A *Merger* is the combination of two or more businesses forming into one entity where the stockholders of the target company offer to seller their shares and invest in the new entity. In the case where a company takes control over another company by purchasing interest and becomes its new owner, it is described as an *acquisition* (Jacob, 2006). The motives for M&A has been widely discussed in research:

"Mergers and acquisitions generally are considered to be rational financial and strategic alliances, made in the best interests of the organization and its shareholders." (Jacob, P. 16 2006)

Thus, M&A may be influenced by the desire to satisfy financial or value-maximizing actions. Nevertheless, research has found some M&A to be non-value adding. An optimal output of an M&A is the maximization of stockholders value, but also to achieve financial synergies (e.g. revenue enhancement and cost reductions). A non-value maximization behavior has been described as hubris by managers, who seek to satisfy their personal motives that are not contributing to economic synergies or to the wealth of shareholders. (Jacob, 2006)

The actors within an M&A transaction are together creating an ecosystem with multiple interactions that are complex. The figure below exhibits various actors involved in an M&A. The actors can be considered as following into one of three categories, (1) internal or company-related actors, (2) external advisors and consultants, and (3) press and regulators. It is essential to understand and manages various parties in order to effectively maximize and shareholders value and to facilitate the M&A process. Understanding the inherent bias and goals of various actors is a prerequisite for executing a strategic transaction. Failing to deal with the ecosystem's complexity and interest would inevitably result in an undesirable completion. (Frankel, 2007)



Actors within M&A (Frankel, 2007)

The figure above exhibits a symmetric distribution of participants within an M&A. On the internal level, both companies have stakeholders with interest on the outcome of the deal, i.e. shareholders, institutions such as venture capitalist and individual investors. And on a lower abstraction level, board of directors, executive management and corporate development team can be found. A sale or an acquisition usually begins with the executive management deciding to initiate the process in order to meet strategic goals. In addition, other functions within the company may be involved in any subsequent part of the M&A; even though the participation might be limited. (Frankel, 2007)

Companies are normally appointing external advisors and consultants for expertise. They usually consist of lawyers, investment bankers, corporate finance experts or other legal institutions. Investment bankers and consultants are often pivotal when assessing a potential deal. The former are usually involved in advising the transaction and to assists with financing. Consultants takes on another role as a facilitator, as they assess the target firm and provide

strategic advice whether to acquire or to reject the offer. Furthermore, they can provide support to facilitate the integration process of the companies. (Frankel, 2007)

Additional independent actors representing the public interest may have interest in the deal. This can for instance be an industry-specific regulator. The manifestation of the deal may be announced to the general society through media channels rather than directly by the companies themselves. (Frankel, 2007)

Due Diligence

Due diligence is a subsequent part of an M&A that aims to address questions whether the deal is carried out at a beneficial time, at the right price and for appropriate reasons. It investigates the affairs of an entity (e.g. a company or a division). A due diligence produces a report explaining relevant details about the entity and its affairs. Many actors and advisers are involved in the process of generating these reports as the process examines several relevant areas of the entity. The process usually investigates the entity from a financial, commercial, legal and environmental standpoint, all of which can be perceived as individual processes.

Although the processes are individually contributing to the evaluation, the financial due diligence has been emphasized as the key part due to its relation to the other areas. The financial part is perceived to contain a lot of wealthy information about the target business. This is due to the fact that it might reveal information that has been neglected by the parties involved in the transaction, for instance unknown synergy or an accounting issue. Undoubtedly a well performed financial due diligence acts as a facilitator and increase the acquirers knowledge of what they are about to invest in. The picture can differ significantly from the initial one as seen by the acquirer compared to the one derived from a well performed due diligence. (Reuvid, 2007)

The Due diligence process has to be managed effectively from the beginning in order to ensure the interest of the parties involved. In order to protect the involved parties, third-party advisers are usually appointed to carry out the due diligence process. (Thomson and Hayes, 2005) When third parties are appointed to act as a facilitators in the due diligence process, acquirers intend to reduce the information asymmetry and related litigation risks between the buyer and seller (Wangerin, 2011).

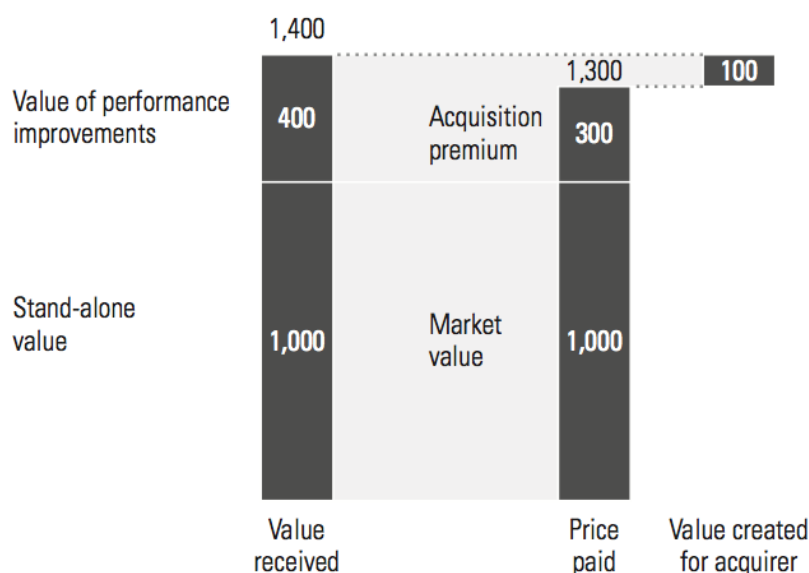
Synergy effects

The process of assessing the accumulated value created by two companies is an essential part in the financial forecast of an M&A. This is explained as *synergies*. Synergies effect the

performance of firms and cannot be obtained in the absence of the transaction (Erchinger and Rowles, 2005). In other words synergies are present when the value created by the transaction exceeds the expected standalone value created by the two independent firms (Mellen and Evans, 2010). In financial terms, Ficery, Herd and Pursche (2007 P.8) define it as:

"The present value of the net additional cash flow that is generated by a combination of two companies that could not have been generated by either company on its own"

The process of discovering and evaluating potential synergies can be approached differently, but generally the process consists of the following subsequent steps; access to external information, information memorandum, management presentations and due diligence. There are essentially four different business combinations that can alter synergies - horizontal integration, vertical integration, concentration- (companies share the same market or capabilities) and conglomeration (combining completely unrelated businesses) transactions (Erchinger and Rowles, 2005). Synergistic benefits derived from business combinations can be generated through revenue enhancements, cost reductions, process improvements, financial negotiations and risk reductions (Mellen and Evans, 2010). The figure below illustrates a simplified calculation of the increased value created through performance improvements (synergies).



Values as a part of an M&A (Koller, Goedhart and Wessels, 2010)

According to Donnell (2013), senior manager at Prother Strategy and Marketing Consultancy, the high premium paid for M&A are no longer justified by cost synergies. Instead the focus

has chanced towards obtaining revenue synergies with aim to fuel business growth. Additionally, revenue enhancement in the context of M&A deserves more attention due to the failure of obtaining anticipated results (Coburn, 2002). Synergies expectations are usually not monetized but instead described as intangible benefits e.g new capabilities, entrance to new market segments and cultural benefits. In order to justify the benefits, synergies have to be quantified and expressed monetarily (Ficery, Herd, and Pursche, B. (2007).

Business valuation and Forecasts within M&A

The implications of an M&A are usually described as real contribution with significant increase in revenues and lower costs through synergies. Contradictory, McKinsey found that 70 percent of M&A fail to obtain their stipulated revenue synergies and 40 percent missed the target of achieving desirable cost reductions (Balsyte & Moeller, 2012). Human behavioral factors in M&A have been widely ignored even though researchers empathize a success rate (in managing to obtain anticipated synergies) of only 30-40 percent. (Moeller & Brady, 2014).

Creating forecasts in a due diligence is commonly linked with estimating the value of a company. Determining the value of a company can essentially be done by three common methods – the value-based, income-based or market-based method. Although, all approaches have being applied under different circumstances in the context of M&A, the market-based has been used most extensively. Furthermore, a more accurate value of a company can be obtained by conjoining the approaches (Siner, 2014). This section will elaborate the most common methods used to value a target company in M&A.

Assets-based approach

Valuing a company on the basis of its *Net assets* is the easiest method as it takes origin in the company's' balance sheet. The value of the subject company is obtained by adjusting the balance sheet through substituting the market value and liabilities of assets from the book value. Additionally, it is placed in relation to owner/shareholders equity (Siner, 2014).

The terminal value of each asset can be calculated separately, where the values reflect the market value of a specific asset. Liquidation costs and taxes are also generally taken into consideration. For an ongoing business, assets are usually valued close to the book value but when the value of an asset has significantly increase or decreased it should be reflected in the balance sheet. The table below exemplifies adjustments made for market value etc. (Tack, 2011).

	Book Value	Adj. To Market	Est. Market Value
ASSETS			
Current Assets:			
Cash & Equivalents	1,817		1,817
Accounts Receivable	2,482		2,482
Inventory	4,555	(1,500)	3,055
Other Current Assets	41		41
Total Current Assets	8,895		7,395
Fixed Assets:			
Building & Land	801	1,699	2,500
Machinery & Equip.	11,069	(7,069)	4,000
Other Fixed Asests	530		530
Less Accum. Deprec.	<u>(8,089)</u>	<u>8,089</u>	<u>0</u>
Net Fixed Assets	4,311		7,030
Other Assets	<u>540</u>		<u>540</u>
Total Assets	<u>13,746</u>	1,219	<u>14,965</u>
LIABILITIES AND EQUITY			
Current Liabilites:			
Line of Credit	695		695
Curr. Portion LT Debt	1,025		1,025
Accounts Payable	527		527
Accrued Liabilities	316		316
Other Current Liabilities	<u>705</u>		<u>705</u>
Total Current Liabilities	3,268		3,268
Long-Term Debt	1,415		1,415
Other Long-Term Liabilities	<u>528</u>		<u>528</u>
Total Liabilities	5,211		5,211
Stockholders' Equity	8,535	1,219	9,754
Total Liabilities & Stockholders' Equity	<u>13,746</u>		<u>14,965</u>

Net asset value summary (Tack, 2011)

When a business has a negative or low value as an ongoing concern, in other words when a company is consistently losing money through negative results, the value-based approach is generally used to determine its value. Even though the company may exhibit negative value its assets might be of substantial value. Applying the assets-based approach will typically result in the lowest valuation of the company, but due to the circumstances it is usually the most appropriate one to use. (Siner, 2014).

Income-based approach

The basis of the income-based approach is to calculate the net present value of future incomes by using a particular discount rate (Siner, 2014). It also refers to the *Discount cash flow model*, which aims to estimate the firm value by computing the present value of cash flows over the company's life. The underlying assumption is that company has finite life, hence the calculation of forecast period and a *terminal value*. The forecast period varies as it should be determined depending on the time interval which the company is estimated to enjoy a competitive advantage (defined as when expected returns exceeds required returns).

Forecasting a time interval of five to ten years is usually applied. The forecast consists of *the free cash flow (FCF)* generated by the company and additional benefits and costs from the transaction. (Schill, Chaplinsky & Doherty, 2000) Applying the methods of free cash flow in the context of M&A should consider the *incremental operating cash flow* associated with the transaction.

Determining the derived value from free cash flows beyond the forecast period is defined as the *terminal value*. The terminal value is estimated at the end of the forecast interval and considers the present value of all future free cash flow. The basis is *the state assumption*, that the company does not experience any abnormal growth or that expected returns is equal to required returns. Moreover, when the free cash flows have been estimated after the forecast interval, the terminal value is determined by using the *Weighted Average Cost of Capital (WACC)* which discounts future cash flows into present value. The cumulative value of the forecast period and terminal value constitutes the estimated value of the company. (Schill, Chaplinsky & Doherty, 2000)

Market-based approach

The market-based approach is the most common one applied when determining the value of a company. The value is determined by comparing some aspects of the focal company to other actors with an established market value. First, it is essential to decide which aspects to compare and thereafter the comparable companies. Comparing the aspects will be a result of the easiness of accessing information. Public companies are obligated to provide access to annual reports, which will facilitate the process. But when a company is operating in a marketplace with non-public companies, valuation might be limited due to less public information. (Siner, 2014)

Comparing any form of earnings is the most common aspect when evaluating companies, but any financial data can be relevant to compare depending on the circumstances. In order to accurately compare financial data between two companies, the same aspects have to be taken into consideration, for instance due to differences in accounting and taxations. A commonly used approach to get a fair comparison is to compare EBITDA, where the subject company's EBITDA is compared in relation to comparable. The output is a factor expressing the average of comparable, which is placed in relation to the subject company to identify weighted values. For example, if the comparable have sold for 5x EBITDA, the target company's value should approximately be 5x its EBITDA. (Siner, 2014).

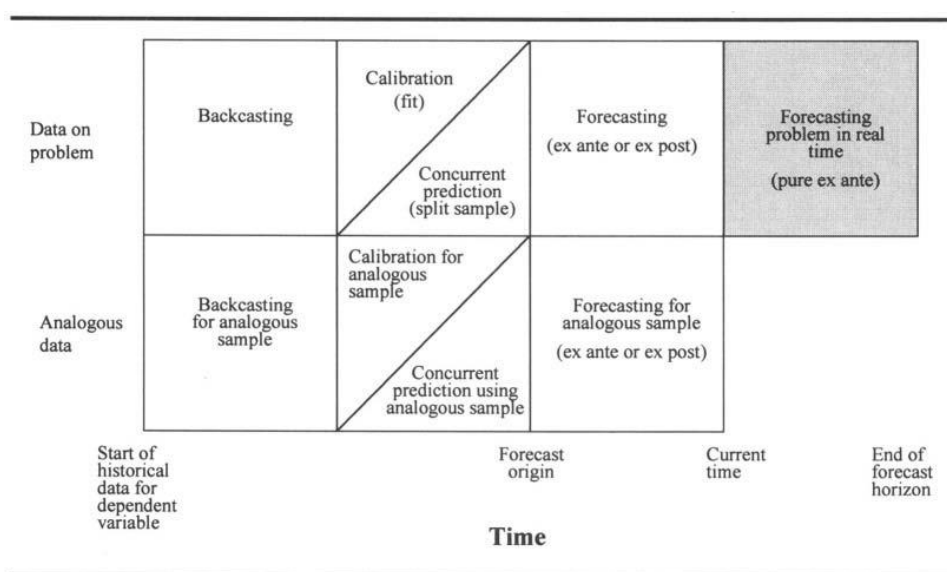
Appendix D – Forecast evaluation

Evaluating forecasts may have several purposes. On the one hand, It may yield insight into the effectiveness of the forecast - To what degree a forecast is the right choice to deal with a particular situation (Hendry & Ericsson, 2003). On the other hand, it may be used to select among several methods or models best fit for the forecasting task at hand (Armstrong, 2001). Finally, the main point of an evaluation may be to detect underlying biases and yield insight to improve its accuracy and lower the associated costs in making it (Gilliland, 2010). The evaluation criterion for a forecasting model should be specific for the purpose of the forecast (Hendry & Ericsson, 2003; Armstrong, 2001). After all, the forecast is created to support some specific decision and was based on a specific set of information. In this regard, it is also necessary to evaluate a forecast in relation to its alternative. There are two fundamental means for evaluating a forecast, by its inputs and by its outputs. Testing the output simply means comparing the forecast to the outcomes and testing the input is everything else. Each offers different insights into the forecasting performance and both are necessary to give a complete picture. (Armstrong, 2001)

Evaluating inputs

Armstrong (2010) presents two steps in the procedure of evaluating input: Testing assumptions and testing data and methods. Specifically, testing the former involves testing the input variables by using different approaches or different sources of data. This is especially relevant for quantitative forecasting methods and adds to the confidence by triangulating uncertainties. He also recommends using objective data when available to the subjective opinions of experts. Another important aspect is to provide a thorough description of the conditions of the forecasting problem and to make sure the forecasting tests are well matched to the problem at hand. For example, when forecasting car sales in a specific region, it would make sense to use data from that region. In many cases however, analogous data is the only reasonable choice. The specific forecasting problems also entail a specific *loss function*, which can be referred to as the various costs of forecasting errors. In general, it is assumed to be symmetric in the sense that an error is equally costly if it is under-forecasted or over-forecasted. In reality, this may not be the case; a simple example proves the point. In forecasting the occurrence of a tornado, it is more costly to the society when forecast "no tornado" if it ends up occurring, than vice versa i.e. forecasting "tornado" when no tornado occurs. (Armstrong, 2001)

The figure below demonstrates how a forecast may be evaluated by using either specific related data or analogous data. In addition, it shows how the available current data may be split into two samples, one for creating the forecast and one to evaluate it. This is sometimes referred to as in-sample data and out-of-sample data testing. By using back casting, it may be possible to test the forecast by forecasting backwards in time and comparing the actual values of the dependent variable. The main issue is whether the forecast created on the current data is relevant for earlier values of the dependent variable. Put differently, are the assumptions and casual relations for the concurrent time period valid for earlier values? Though, perhaps even more importantly is whether the findings from a back casting endeavor are any useful in indicating an actual forecast. (ibid)



Forecasting as carried out over different time periods (Armstrong, 2001)

Apart from checking the assumptions of the forecast, Armstrong (2001) explains how to analyze data and methods. Main features of this approach involves checking for simple data errors to ensure its reliability and validity, to search for potential biases in the method of generating the forecast and to ensure the forecast model is well understood by all the parties involved. Gilliland (2010) mentions issues with using input data to forecast demand in an organization. The "true" demand is never known since customers may use "gamesmanship" for their own benefit. For example, they may inflate or withhold orders based on their perception of shortages or competitive offers. His key point is that any measures to improve the demand forecast will at some point be futile since it will always entail the error stemming from the unobservable true demand. (Gilliland, 2010) On a more general note, Diebold (2006, p.260-261) writes:

"... This highlights the inherent limits to forecastability, which depends on the process being forecast; some processes are inherently easy to forecast while others are hard to forecast. In other words, sometimes the information on which the forecast conditions is very valuable, and sometimes it isn't."

Evaluating output

When it comes to evaluating output, Armstrong (2001) mentions two ways. The first involves doing replications. By using combinations the same/different methods with same/different data it is possible to make comparisons between the outcomes. If they prove to agree then this ought to strengthen the validity of the forecasting model. If there were any disagreements, it would be easy to spot simple errors since it is unlikely for different forecasters to make the same mistake. Moreover, it assesses the reliability of the forecasting method over time and place, and may test its usability in a different contexts, thus assessing the generalizability of the forecast method. (Armstrong, 2001)

The second way is to directly assess the output. Armstrong (2001) again mentions the key points in this regard. Firstly, he recommends including all criteria necessary. Most important may be the accuracy, but several other measures provides additional information. Secondly, he mentions the importance of pre-specifying criteria to avoid falling trap to the confirmation bias. It is too common for people to misinterpret or reject findings if it does not confirm their forecasts. (Armstrong, 2001) Finally, he ends with discussing *face validity* as a quick test of the reasonability of the forecast. Although, there is a risk of falsely judging a correct forecast as incorrect if the forecast method is unusual or unfavorable (Armstrong, 2001).

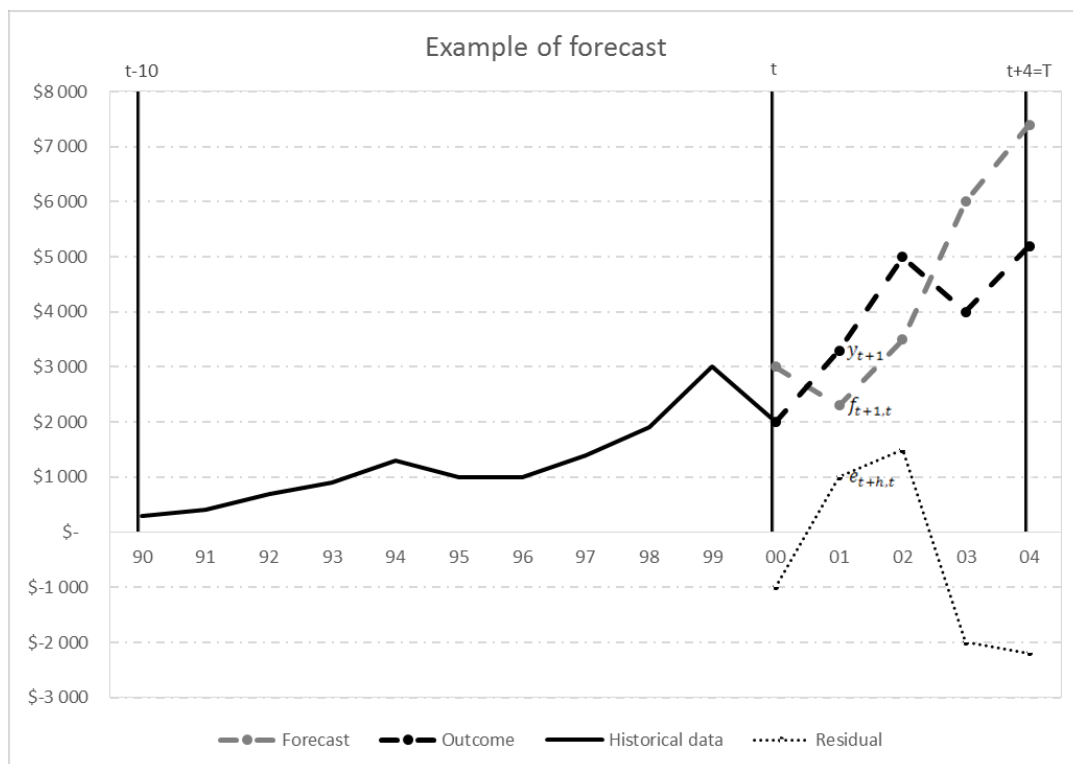
Forecasting error measures

The chapter will introduce a mathematical framework and denote the components used in assessing the output quantitatively. First off, assume the known outcomes of a time series as y_1, \dots, y_{t_0} , representing the *in-sample data*. The future outcomes are denoted y_{t_0+1}, \dots, y_T , representing the *out-of-sample data* with a forecast horizon T . A forecast can be denoted as f_{t,t_0} for time t , created at time t_0 . Specifying t_0 is important since it confirms what information was available at the time of making the forecast. Given that, the *forecast error* or *residual* at any time t can be denoted as:

$$e_t = y_t - f_{t,t_0}$$

In general, when creating a model based on y_1, \dots, y_{t_0} and comparing it to the same data, we have an in-sample forecast. This is generally more accurate than an out-of-sample forecast (based on y_1, \dots, y_{t_0} but compared to y_{t_0+1}, \dots, y_T) since is specified precisely on that data's characteristics.

The figure below shows an illustration of an example forecast. When the difference in performance between the two forecasts is significant, it may be owing to model *over-fitting*. This means that the forecast model is failing to generalize beyond the known outcomes because part of the model captures its unique features to the specific data rather than the forecasted object as a whole (Diebold, 2006). When analyzing residuals, Diebold (2006) discusses the important notion of the “*unforecastability principle*”, which says that systematic patterns in the residuals implies an imperfect forecast. Equivalently, an ideal forecast should not have predictable forecast errors. This is based on the idea that if the forecast errors are predictable, they can be forecasted themselves and adjusted for, thus improving the forecast by reducing its errors. (Diebold, 2006)



Example of a forecast, historical data, outcome and residuals

The residuals then are the key to understanding and hopefully find ways to improve the forecast performance. Naturally, it is common to analyze the distribution of residuals and illustrate them in *residual plots*.

The first common measure is the first moment, the mean. Here, the *Mean Error* can be defined as (note that all measures below are defined for the out of sample case):

$$ME = Mean(e_{t_0+t, t_0}) = \frac{1}{T - t_0} \sum_{t=1}^T e_{t_0+t, t_0}$$

This is the most straightforward measure of forecast bias. An alternative measure is using the *Median Error*. By first assuming that the residuals e_{t_0+1}, \dots, e_T are ordered, the median error then becomes:

$$MdE = Median(e_{t_0+t, t_0}) = \begin{cases} \frac{e_{T+1}}{2} & \text{if } T - t_0 \text{ is odd} \\ \frac{e_{\frac{T+t_0}{2}} + e_{\frac{T+t_0}{2}+1}}{2} & \text{if } T - t_0 \text{ is even} \end{cases}$$

It may be necessary in some cases to use a measurement that is comparable across different time-series. Thus, the *Mean Percentage Error* can be defined as:

$$MPE = Mean(p_{t_0+t, t_0}) = \frac{1}{T - t_0} \sum_{t=1}^T \frac{e_{t_0+t, t_0}}{y_{t_0+t}}$$

Similarly, *Median Percentage error* are defined by ordering the scaled errors $\frac{e_{t_0+1}}{y_{t_0+1}}, \dots, \frac{e_T}{y_T}$:

$$MdPE = Median(p_{t_0+t, t_0}) = \begin{cases} \frac{\frac{e_{T+1}}{y_{T+1}}}{2} & \text{if } T - t_0 \text{ is odd} \\ \frac{\frac{e_{\frac{T+t_0}{2}}}{y_{\frac{T+t_0}{2}}} + \frac{e_{\frac{T+t_0}{2}+1}}{y_{\frac{T+t_0}{2}+1}}}{2} & \text{if } T - t_0 \text{ is even} \end{cases}$$

It is possible to define similar measures based on the geometric mean, but it is relatively rare when analyzing forecast. All the above-mentioned measures capture forecast bias, however that only accounts for a part of the truth. Another important measure is the *Forecast Variance*, which is defined as:

$$FV = Var(e_{t_0+t, t_0}) = \frac{1}{T - t_0} \sum_{t=1}^T (e_{t_0+t, t_0} - ME)^2$$

Taking the root results in the standard deviation, which offers better interpretability.

$$FSTD = \sqrt{Var(e_{t_0+t, t_0})} = \sqrt{\frac{1}{T - t_0} \sum_{t=1}^T (e_{t_0+t, t_0} - ME)^2}$$

Moreover, one can check higher moments by analyzing the skewness and kurtosis of the residuals. In fact, Gu and Wu (2003) found that by forecasting the median, the accuracy may be increased and in the case of skewed distributions for the forecasted object, such result would generate forecast bias. The skewness is defined as the cubed deviation from the mean:

$$S = \frac{1}{T-t} \sum_{i=1}^T (e_{t_0+t, t_0} - ME)^3$$

For completion, the fourth moment, kurtosis can be used to analyze the thickness of the tail of a distribution, and may be useful to compare whether a tail is thicker or thinner than the regular tail of a normal distribution. It looks as follow:

$$K = \frac{1}{T-t} \sum_{i=1}^T (e_{t_0+t, t_0} - ME)^4$$

While these equations enable understanding of the distribution, it does not tell anything about dependencies over time. These are important in order to improve a forecast by learning from mistakes made in the past and adjusting future forecast endeavors. Thus, the so-called *Autocorrelation* (also called *Serial Correlation*) is used to measure correlation in time series. In particular, the *Autocorrelation function* is a scaled version of the *Auto covariance function* and can in general be defined as:

$$\rho(s, t) = \frac{Cov(e_s, e_t)}{\sqrt{Var(e_{s, t_0})} \sqrt{Var(e_{t, t_0})}}$$

Where $Cov(e_s, e_t)$ is the autocovariance function. Here, s and t represent two different time points. If assuming the function is second-order stationary and specifying it for forecast purposes, it can be written as:

$$\rho(\tau) = \frac{Mean(e_{t, t_0} - ME)(e_{t+\tau, t_0} - ME)}{FV}$$

Thus, the function measures correlation between e_{t, t_0} and $e_{t+\tau, t_0}$. It takes values in $[-1, 1]$ and yields information of the correlation of the times series on itself. Following the argument of the unforecastability principle, the autocorrelation function should not be statistically significant if the forecast is optimized. Sometimes, the *Partial Autocorrelation Function* is used instead and differs only in that it measures the correlation *after* any linear dependence has been removed. The functions are useful to plot as they immediately illustrate any dependencies in the time series by a simple visual check. Statistically, the existence of

autocorrelation in a time series can be assessed through a Durbin-Watson statistic test defined as follows:

$$DW = \frac{\sum_{i=2}^T (e_{t_0+i,t_0} - e_{t_0+i-1,t_0})^2}{\sum_{i=1}^T e_{t_0+i,t_0}^2}$$

It take values in $[0,4]$ and should ideally lie around 2. When falling below 1,5 there is reason suspect bias (Diebold, 2006). See the figure below for an example of an autocorrelation *plot*.



Measures (sales)			
Mean	20,9	Kurtosis	-0,9
Median	20,5	Min	9
Variance	42,3	Max	35
Skewness	0,1	Number	52

Measures (residuals)			
Mean	0,2	Kurtosis	0,5
Median	0	Min	-9
Variance	12,5	Max	9
Skewness	0,1	Number	51

Sales numbers, distributions, autocorrelation functions and descriptive statistics.

Returning to the measure of forecast performance, the forecast bias and forecast variance together make out the *Forecast Accuracy*. Both are preferably minimized to maximize the accuracy of the forecast. Several measures of forecast accuracy are used in practice and using several is recommended as they provide different information (Armstrong, 2001). In a similar manner to earlier, one can define measures based on the mean or the median and on percentage errors or residuals straight away. The most common one is the mean squared error (Diebold, 2006). It is defined as:

$$MSE = Mean(e_{t_0+t,t_0}^2) = \frac{1}{T-t} \sum_{t=1}^T e_{t_0+t,t_0}^2$$

Equivalently, the *Mean Squared Percent Errors* is:

$$MSPE = Mean(p_{t_0+t,t_0}^2) = \frac{1}{T-t} \sum_{t=1}^T \left(\frac{e_{t_0+t,t_0}}{y_{t_0+t}} \right)^2$$

To preserve the units and offer better interpretability, the *Mean Absolute Error*, the *Root Mean Squared Error*, the *Mean Absolute Percentage Error* and the *Root Mean Squared Percentage Errors* are respectively defined as (the median measures are defined correspondingly to above):

$$MAE = Mean|e_{t_0+t,t_0}| = \frac{1}{T-t} \sum_{t=1}^T |e_{t_0+t,t_0}|$$

$$RMSE = \sqrt{Mean(e_{t_0+t,t_0}^2)} = \sqrt{\frac{1}{T-t} \sum_{t=1}^T e_{t_0+t,t_0}^2}$$

$$MAPE = Mean|p_{t_0+t,t_0}| = \frac{1}{T-t} \sum_{t=1}^T \left| \frac{e_{t_0+t,t_0}}{y_{t_0+t}} \right|$$

$$RMSPE = \sqrt{Mean(p_{t_0+t,t_0}^2)} = \sqrt{\frac{1}{T-t} \sum_{t=1}^T \left(\frac{e_{t_0+t,t_0}}{y_{t_0+t}} \right)^2}$$

Using the absolute rather than the squared errors will mean that extreme values are punished less severely.

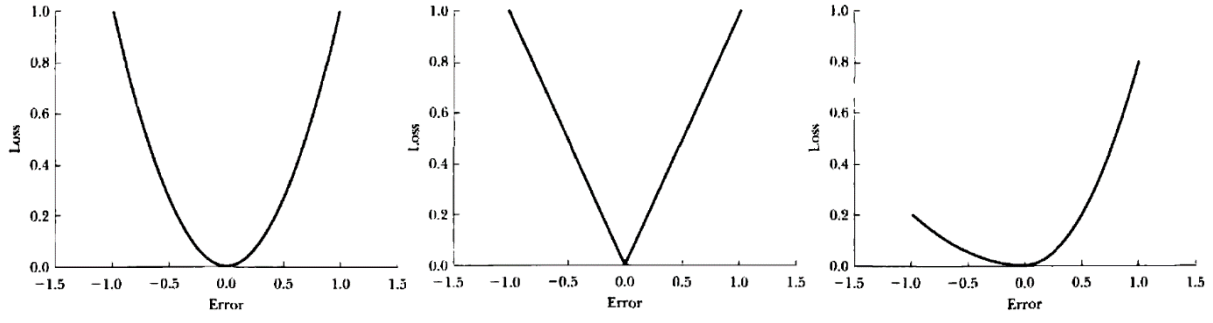
These measures have one thing in common in that they assume a symmetrical loss function. This was mentioned earlier, whereas the illustrative example of a tornado forecasting indicates that assuming such symmetry may not be correct. Or rather, if the goal was to maximize the forecast accuracy then it would have been better to always forecast “no tornado”. Of course, such a forecast would have no value. Hence, in the case of asymmetrical loss functions, the above-mentioned measures of accuracy may not be very useful since it treats under-forecasting and over-forecasting alike (Balakrishnan, 2010). In reality, an ideal forecast is then not about maximizing the forecast accuracy but about minimizing the loss function (Diebold, 2006). This function can be denoted $L(e)$ since it depends solely on the size of the residual. Diebold (2006) reveals three conditions of the loss functions that need to be satisfied.

$$L(0) = 0$$

$L(e)$ is continuous

$L(e)$ is increasing on either side of the origin

The figure below gives a few examples of loss functions, the first two being symmetrical (Diebold, 2006). Since the true loss function is rarely known, applying the symmetrical loss function assumption is still common practice (Balakrishnan, 2010). The key take away from this is that it may result in over-forecasting or under-forecasting and consequently in forecast bias.



Examples of loss functions (Diebold, 2006)

Several measures of accuracy suffers from additional problems. Koehler and Hyndman (2006) goes into detail and recommends their own measure to account for these issues. They noticed some methods (e.g. MSE, MAE, RMSE) are dependent on the scale of the time series and thus not useful if comparing among series with different scales. Other, scale independent measures (e.g. MSPE, MAPE, RMSP) generated undefined, infinite values or heavily skewed distributions when the outcomes had zeros or values close to zero. In addition, these measures offer little interpretative value for measuring temperature etc.

An adjusted form was created called symmetric mean absolute percentage error defined as:

$$sMAPE = \frac{1}{T-t} \sum_{t=1}^T 200 \frac{|y_{t_0+t} - f_{t_0+t, t_0}|}{y_{t_0+t} + f_{t_0+t, t_0}}$$

This measure can still take on negative values and (in spite of the wording) is unsymmetrical in the sense that it punishes over forecast and under forecast differently (Koehler and Hyndman, 2006). Yet another option is to use relative errors, where the errors are scaled according to a benchmark method. For example, the error associated with the naïve forecast of using the value for the current period to forecast the next value, a so called *Random Walk*. This benchmark is useful because it indicates the performance of a forecast without any effort put into it. It is a purely mechanical calculation. Alternatively, one may use relative measures rather than relative errors. For example, by calculating $MAE/MAE_{benchmark}$. The specific case of $RMSE/RMSE_{random\ walk\ benchmark}$ in one-step ahead forecasts is actually called the Theil's U statistic. The measures offer good interpretability since it is easy to compare to the benchmarks. But it still suffers from the scale dependence.

The authors presents scaled errors, and in particular the *Mean Scaled Absolute Error*:

$$MASE = Mean|q_{t_0+t, t_0}| = \frac{1}{T-t} \sum_{t=1}^T |q_{t_0+t, t_0}| = \frac{1}{T-t} \sum_{t=1}^T \left| \frac{e_{t_0+t, t_0}}{\frac{1}{t-1} \sum_{i=2}^t |y_i - y_{i-1}|} \right|$$

It is essentially the mean of the out-of-sample errors scaled by the mean of the in-sample errors from a random walk. They argue that it is suitable for comparing accuracy across multiple time series. The measure is less than one if the forecast performs better than the benchmark and vice versa. (Koehler and Hyndman, 2006)

The table below summarizes the error measures. The list is not exclusive. In particular, the measures may involve the geometric mean rather than the mean or median. Other methods have tried other ways to normalize the common errors associated with scale dependence, such as the *Normalized Root Mean Square Error* (nRMSE).

Measures of bias and accuracy

	Mean	Mean percentage	Median	Median percentage
Error (bias)	ME	MPE	MdE	MdPE
Square errors	MSE	MSPE	MdSE	MdPSE
Root Squared errors	RMSE	RMSPE	RMdSE	RMdSPE
Absolute errors	MAE	MAPE	MdAE	MdAPE
Symmetrical		sMAPE		sMdAPE
Relative error		MRAE		MdRAE
Relative measure		RelMAE		RelMdAE
Scaled		MASE		MdASE

A non-exhaustive list of errors measures.

Appendix E – Industry Categorization SNI 2007

A - Agriculture, forestry and fishing

B - Mining and quarrying

C - Manufacturing

D - Electricity, gas, steam and air conditioning supply

E - Water supply; sewerage, waste management and remediation activities

F - Construction

G - Wholesale and retail trade; repair of motor vehicles and motorcycles

H - Transportation and storage

I - Accommodation and food service activities

J - Information and communication

K - Financial and insurance activities

L - Real estate activities

M - Professional, scientific and technical activities

N - Administrative and support service activities

O - Public administration and defense; compulsory social security

P - Education

Q - Human health and social work activities

R - Arts, entertainment and recreation

S - Other service activities

T - Activities of households as employers; undifferentiated goods- and services producing activities of households for own use

U - Activities of extraterritorial organizations and bodies

Appendix F – Ohlson's score

The variables below exhibit the original independent variables used by Ohlson (1980) to measure the probability of bankruptcy. Given the acronyms expressed by Ohlson (1980), the variables can be understood by considering them individually. The O-score can later be transformed into a probability through *the probability of failure formula* (Hillegeist, et al 2004; Mitchell and Walker, 2008). This equation measures the probability of bankruptcy and always falls between 0 percent and 100 percent. Price level index has been adjusted to fit the focal study.

SIZE = Log (total assets/GNP price-level index). GNP price level index is based on values from 2004 and are assigned 100 as a reference since the first forecast was issued during this year. Moreover, total assets are expressed in dollars for the year the forecast was issued.

TLTA = Total liabilities / Total assets

WCTA = Working capital / Total assets

CLCA = Current liabilities / Current assets

OENEG = 1 if total liabilities exceeds total assets, else 0

NITA = Net income / Total assets

FUTL = Funds from operations pretax before depreciation/ total liabilities

INTWO = 1 if net income was negative for the last two years, else 0

CHIN = (NIY-NIY-1)/ (ABS(NI year Y)+ABS(NI year Y-1)), intend to measure change in net income.

Step 1

$$O - Score = -1.32 - 0.407 * \ln\left(\frac{total\ assets}{GNP\ price\ level\ index}\right) + 6.03 * \left(\frac{total\ liabilities}{total\ assets}\right) - 1.43 * \left(\frac{working\ capital}{total\ assets}\right) + 0.076 * \left(\frac{current\ liabilities}{current\ assets}\right) - 1.72 * (1\ if\ total\ liabilities > total\ assets, else\ 0) - 2.37 * \left(\frac{net\ income}{total\ assets}\right) - 1.83 * \left(\frac{funds\ from\ operations}{total\ liabilities}\right) + 0.285 * (1\ if\ net\ loss\ for\ last\ two\ years, else\ 0) - 0.521 * \left(\frac{net\ income\ y - net\ income\ y-1}{|net\ income\ y + net\ income\ y-1|}\right)$$

Step 2

$$Probability\ of\ failure = \frac{e^{O\ score}}{1 + e^{O\ score}}$$