UNIVERSITY OF TURKU

ABSTRACT

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Abstract

Academia is unanimous that abnormal returns can be achieved if takeover targets are perfectly identified in advance of the takeover. Scholars and investment professionals have studied takeover prediction since 1970s. So far, the results have been modest. This thesis's objective is to construct as accurate and as reliable takeover prediction model as possible by employing new data set in terms of geography and time frame than in previous literature. In addition, new variables are introduced, and comparison of statistical models done.

An extensive data set of 17 476 observations is used, including 702 target companies and 16 774 non-target companies. The data set covers all the four Nordic countries as well as Germany and France. Time frame of the research is from 2001 to 2018. Thus, many different macroeconomic conditions are included in the study. The models are mainly based on financial data of companies. This thesis is among the first studies to incorporate firm specific financial data, industry specific data as well as macroeconomic data into the regression models. In total, eight regression models are constructed and run. Four of them are simple logistic regression and four are conditional logistic regression. As the simple logistic regression and conditional logistic regressions are run concurrently, power of conditional matching by year and industry is analyzed.

Seven out of the ten introduced hypotheses are confirmed, and many variables are found highly statistically significant and reliable. This study finds target companies to be smaller by size, more expensive by valuation multiples and more leveraged than non-target companies. Furthermore, target companies outperform non-target companies in terms of liquidity and investments in capital expenditures. It is also found that companies which operate in industry where acquisitions have occurred previous year and companies which are located in a country where macroeconomic condition is positive in terms of GDP growth, are more likely to become takeover targets.

The best performing model of this thesis is able to correctly classify firms to targets and non-targets at 60.01 % probability. The model correctly predicts 63.20% of targets and 59.79% of non-targets in out of-sample tests.

Key words	Mergers & Acquisitions, Takeover prediction, Conditional Logistic Regression

TURUN YLIOPISTO

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Tiivistelmä

Akateemikot ovat yksimielisiä siitä, että epänormaalit tuotot voidaan saavuttaa, jos yritysostokohteet yksilöidään täydellisesti ennen ostotarjouksen julkaisemista. Tutkijat ja muut sijoitusammattilaiset ovat tutkineet yrityskauppojen ennustamista 1970-luvulta lähtien. Toistaiseksi tulokset ovat olleet vaatimattomia. Tämän tutkielman tavoitteena on rakentaa mahdollisimman tarkka ja luotettava yrityskauppojen ennustamismalli. Tämä suoritetaan käyttämällä erilaista maantieteellistä ja ajallista otosta koskevaa dataa kuin aikaisemmassa kirjallisuudessa. Lisäksi otetaan käyttöön uusia muuttujia ja eri tilastollisia malleja käytetään yhdessä.

Opinnäytetyö käyttää laajaa aineistoa, joka sisältää yhteensä 17 476 havaintoa, mukaan lukien 702 yritysoston kohdetta ja 16 774 ei-yritysoston kohdetta. Aineisto kattaa kaikki neljä Pohjoismaata sekä Saksan ja Ranskan. Tutkimuksen ajallinen otos alkaa vuodesta 2001 ja päättyy vuoteen 2018. Täten, tutkimukseen on sisällytetty monia erilaisia makrotaloudellisia olosuhteita. Mallit perustuvat pääosin yritysten taloudellisiin tietoihin. Tämä opinnäytetyö on yksi ensimmäisistä tutkimuksista, joissa on yhdistetty yrityskohtaisia taloudellisia tietoja, toimialakohtaisia tietoja sekä makrotaloudellisia tietoja regressiomalleihin. Yhteensä kahdeksan regressiomallia rakennetaan. Näistä neljä on yksinkertaista logistista regressiota ja neljä ehdollista logistista regressiota. Koska mallit ajetaan samanaikaisesti, ehdollisen sovittamisen tuomaa mahdollista hyötyä ennustetarkkuuteen voidaan analysoida.

Seitsemän kymmenestä esitetystä hypoteesista vahvistetaan, ja monet muuttujat ovat erittäin tilastollisesti merkittäviä ja luotettavia. Tämän tutkimuksen mukaan kohdeyritykset ovat kooltaan pienempiä, arvostuskertoimien perusteella kalliimpia ja enemmän velkaisia. Lisäksi kohdeyritykset ovat likviditeetiltään vakaampia ja käyttävät suhteessa enemmän rahaa investointeihin kuin ei-yritysostokohteet. Tämä tutkimus myös löytää yrityksien, jotka operoivat yrityskauppa-aktiivisella toimialalla sekä yrityksien, jotka sijaitsevat maassa, jossa BKT on kasvava, olevan todennäköisemmin yritysoston kohteena.

Opinnäytetyön parhaiten toimiva malli pystyy ennustamaan tulevan yrityskaupan todennäköisyydellä 60,01%. Malli ennustaa oikein 63,20% yritysostokohteista ja 59,79% ei-yritysostokohteista aineiston ulkopuolelle jäävällä datalla.

Avainsanat	Yrityskaupat & Fuusiot, Yrityskauppojen ennustaminen, Regressioanalyysi

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PREDICTABILITY OF M&A TARGETS

Empirical evidence from Nordic and Central Europe

Master's Thesis
in Accounting and Finance

Author:
Kristian Vuorenvirta

Supervisors:
Prof. Mika Vaihekoski
M.Sc. Valtteri Peltonen

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1 INTRODUCTION

1.1 Background and motivation

Today's world is changing; today's business is changing. Yet one thing has not changed, firms desire to grow. A firm has three different ways to seek growth; organically, through innovation and through acquisitions. Organic growth is seen difficult and slow. It can take several years to reach an intended size in constantly faster changing environment. On the other hand, growth through innovation is seen rather expensive and risky option. Growth through acquisition is seen to be the best alternative to grow fast. It gives immediate access to acquired firm's tangible and intangible assets and creates synergies. In addition, bigger size enables to achieve better market position and survive in instable macroeconomic environment. (Lees 2003, 3)

Due to these advantages of acquisitions, M&As, i.e. mergers and acquisitions have become more and more popular as an essential part of the strategy in companies. On account of these strategies already big national companies have become giant multinational companies. For instance, in the United States 50 largest Multinational Enterprises (MNEs) control over one fourth of total US corporate assets. These companies are drivers of world economy and they have more power and influence than some United Nation member states. (Lees 2003, 3-4)

As M&As are proven to be successful parts of growth strategies, it is no wonder that M&A activity is increased significantly during last decades. To put the words into numbers, in 2007, the record year of worldwide M&A activity by value, value of deals in US dollars reached a sum of 4,9 trillion. (Farrell 2015, 1). To compare, in 1985 the value of M&A deals was only 347 billion US dollars. In other words, activity of mergers and acquisitions in value were over 14 times bigger in 2007 than in 1985. Furthermore, the fact that global M&A activity has recovered from financial crisis and it has reached new records year after year in the abnormal macroeconomic environment brings topicality to the subject. (Institute for Mergers, Acquisitions and Alliances 2019)

There is no simple answer to the question why mergers and acquisitions happen. There are several micro level motives and macroeconomic factors that have effect on management's desire to exploit M&A as part of a company's strategy. Micro level motives are fundamental reasons why M&As take place in companies. However, macroeconomic factors have a huge impact on the M&A activity in global and local scale. In other words, the motives for M&As are there all the time, but macroeconomic factors either ease or hinder a firm's possibilities engage with mergers and acquisitions.

It is essential to understand the difference between micro and macro forces in the framework of M&A. Microeconomics focuses on the individual actors of the economy, such as firms and management, whereas macroeconomics has its emphasis on the behavior of the economy as a whole. (Pohjola 2012, 289-290) Bernstein (2009,1) states in general level that micro and macro forces are not separate from each other, they rather create an interactive and deep relationship with each other. Similarly, in M&A context, Choi and Jeon (2011, 235) argue that microeconomic motives are fully or partially driven by macroeconomic environment.

As the forces behind mergers and acquisitions are arguably ambiguous, this thesis's ambition is to study these forces in more detail. Thus, employment of regression models is in place to further study the micro level, firm specific factors, as well as macro level factors behind M&A. Many regression models, such as logistic regressions, provide framework to study these factors, but framework for classification among M&A targets and non-targets is provided as well by such models. In other words, if one is fully able to understand the factors behind mergers and acquisitions, the one is also able segregate firms which will be taken over and firms which will not be taken from each other. This classification is the basis for successful takeover prediction, this thesis ultimate objective.

Capability to successfully predict acquisition targets is valuable in many ways. Firstly, numerous studies have shown that the share price of the targets increases around the period of the announcement date. Thus, holding a portfolio of targets would undoubtedly be a good investment strategy with high abnormal returns. Secondly, policy makers are in need of predictability of M&A targets in order to protect public interest with all negative factors related to M&A. Therefore, this thesis´s ambition is to develop a model to predict M&A targets. Predictability of M&A targets is a widely studied subject, but much less research has been devoted to smaller geographical areas such as the Nordics. Furthermore, past models have focused mainly in variables linked to financial ratios, i.e. micro level factors. My ambition is to enhance the predictability accuracy by embedding certain macroeconomic variables into model as well as they are directly linked to M&A activity and tend to be more up-to-date information than financial variables in general.

1.2 Research question, empirical approach and data

This goal of this thesis is to research predictability of mergers and acquisitions. The main objective is to develop a takeover prediction model, which is accurate and reliable. In addition, potential differences based on accounting data among target firms and non-target firm will be analyzed. This thesis employs an extensive set of financial data. The data set consists of 17 476 observations which include 702 target companies and 16 774 non-target companies. Every observation contains all financial data needed for variables used in regression models. The overall data is divided into two sections; estimation section and prediction section. Estimation section consist of 13 797 observations from 2001 to 2014, whereas prediction section's 3 681 observations are from 2015 to 2018. All the variables used by regression models are validated by estimation section's data. Prediction accuracy, on the other hand, is determined by prediction section's data as out-of-sample tests are based on this data set. This thesis employs both simple logistics regression models as well as conditional logistic regression models in order to find the most relevant variables behind acquisitions and to achieve high and reliable prediction results. The two types of models are run concurrently with each other in order to detect possible differences in models' prediction power and statistical reliability.

1.3 Contribution

This thesis contributes to the existing takeover prediction literature in four ways. Firstly, geographical area of study is expanded to cover the Nordic countries, which have lacked academics' attention within takeover prediction literature. The Nordic countries are studied alongside with two large European countries, Germany and France to have a large amount of observations ensuring reliable study. Secondly, exceptionally long and comprehensive data set is employed covering all the years from 2001 to 2018. This long-time frame incorporates many exceptional macroeconomic periods such as the dotcom bubble, the financial crisis, long recovery from the financial crisis in historically low interest rate environment as well as the European debt crisis. Thirdly, macroeconomic aspect of mergers and acquisitions is included in this thesis. The aspect is studied country by country basis in order to find how different macroeconomic conditions of countries affect acquisition likelihood in a firm level. Fourthly, the empirical approach of the study is extended. In previous takeover prediction literature academics have chosen only one statistical model to study the subject. Unlike previous literature, this thesis uses two different models concurrently. Thus, prediction power and statistical reliability of different models can be analyzed in more depth.

1.4 Structure

The thesis is structured as follows: Chapter 2 studies theoretical background of mergers and acquisitions as it provides a brief overview of merges and acquisitions, types of M&A, micro level motives and macro level factors behind mergers and acquisitions. Chapter 3 will go through the existing academic literature on M&A predictability focusing on methodological developments within the field and the prediction variables including both financial ratios and macroeconomic variables. Data and all the hypotheses linked to the study are analyzed in detail in the Chapter 5. Regression models are constructed in the Chapter 5, fully based on the Chapter 4 findings. Prediction accuracy tests are as well conducted in the Chapter 5. Conclusions of the thesis are provided in the Chapter 6.

2 THEORETICAL BACKGROUND

2.1 Overview of mergers and acquisitions

Roberts et al. (2012, 2) have defined mergers and acquisitions as the combination of two or more companies into one new company. However, merger and acquisition are no synonyms, even though the literature often discuss them as such. (e.g. Eckbo 1983, Cugler et al. 2003) Merger occur when two or more companies of approximately equal size merge into one company. In case of a merger, no cash nor stocks need to be exchanged in order to seal the deal, as in an acquisition where a firm is buying, with cash or stocks, another company. After the transaction is made, the acquired company, the acquiree, becomes part of the acquirer. As a difference in mergers, acquisitions most likely take place in the framework of companies that are not equal size. In other words, a small company is acquired by a larger company. (Rompotis 2015, 34) Furthermore, it is noteworthy to comprehend the differences in volume between mergers and acquisitions. Mergers are not as common as acquisitions. In fact, only 3% of all mergers and acquisitions are mergers. (Peng 2009, 331) However, in both cases there are only one company left as Roberts et al. (2012) stated above. Therefore, the definitions can be used together as general definition, M&A.

Majority of scholars have divided acquisitions into three groups. (e.g. Pickering, 1978, Roncevik 2008, Horst 2009, Herger & McCorriston, 2014). The first type of acquisition is horizontal acquisition, where the involved companies come from the same industry. The objectives of horizontal acquisition are often linked to stronger market position or taking advantages of economies of scale. It is relatively easy to meet these objectives when the companies come from the same industry and are similar with each other. The second type of acquisition is vertical acquisition, where the involved companies come from the same industry but from different stages of the production chain. The objective is to get the control of distribution channel in order to provide better quality or to have better pricing options. The first two types of acquisitions occur in the same or related industry. Whereas the third type, conglomerate acquisition, occurs in unrelated industry. Although there might be some synergy and scale benefits, that is not the main objective. In the framework of conglomerate acquisitions, companies either pursuit faster growth from another industry or share its risks by not having all the eggs in the same basket. (Horst 2009, 762, Mcgrath 2011, 10-11)

According to Pickering (1978, 129) horizontal acquisitions both in volume and value are represented as the most general option by far. On the other hand, Herger and McCorriston (2014, 1-2) have stated that a clear majority of cross-border acquisitions are conglomerate acquisitions. Although Herger and McCorriston are writing in the context of cross-border acquisitions whereas Pickering is writing from national approach, it must be remembered that a significant part of all today's M&A activity is precisely from cross-border acquisitions, which have increased tremendously over last decades due to globalization. (Zou 2012,1). For instance, in 2015 36% of total M&A in value and 31% of total M&A in volume were from cross-border acquisitions. (jpmorgan.com/M&A) Therefore, it can be stated that the role of conglomerate M&As have increased alongside with cross-border acquisitions from the end of 1970s.

Rompotis (2015, 35-38) has moreover listed other categorizations and dimensions in the context of M&A. Firstly, M&As can be either private or public. If the acquired company is publicly listed, the acquisition is public and vice versa. Secondly, M&As can be either friendly or hostile. A friendly acquisition occurs when the target company is willing to sell, whereas a hostile acquisition take place against acquired company's desire or knowledge. Thirdly, generally acquisitions are made by larger company, but sometimes acquisitions occur the other way around, when a larger company is acquired by a smaller one. This kind of acquisition is known as reverse takeover. Furthermore, terms "acqui-hiring'' and "leveraged buyout" (LBO) represent other dimensions as above mentioned. Acqui-hiring, which is widely spread phenomenon among high-tech firms, takes place when usually smaller company's key-employees are acquired to a bigger company. (Chatterji & Patro 2014, 395) Leveraged buyout is an acquisition where a target company, public or private, is bought into a private company by private investors in order to achieve stockholder gains, tax savings and operative effectiveness. The difference between a normal acquisition and LBO is the amount of borrowed funds, which makes LBO riskier. (Smith 1990, 19.)

2.2 Micro level motives

Micro level motives explain the fundamental reasons why firms engage in mergers and acquisitions. Therefore, it is crucial to understand these micro level motives from theoretical approach. Although Baker et al (1981,1) argue that the main motive for M&A is the economic growth and similarly Basmah and Rahatullah (2014,182) state that firms participate in mergers and acquisitions in order to achieve economic gains the motives are not always as black-and-white. This Chapter takes a stand on multiple different motives with multiple approaches and dimensions on the question why firms engage in M&A.

There is a great variety of different kind of motives behind mergers and acquisitions. Perhaps the best known and mostly cited classification of M&A motives among scholars is Trautwein's seven theories. As defining the motives, he takes into account multiple different approaches such as shareholders' interest, managerial interest, mergers as a process and mergers as a macroeconomic phenomenon. In other words, micro level motives and macroeconomic factors are both considered. This Chapter focuses on the former and the next Chapter has its emphasis on the latter. Moreover, according to many scholars (e.g. Steiner, 1975, Ravenscraft & Scherer, 1987) no theory nor motivation can merely explain mergers and acquisitions. However, due to a scientific perspective, theories are approached individually and mutually exclusively (Trautwein 1990, 283). Table 1 provides an overview of the different types of dimensions between acquisition motives.

Table 1 Seven theories of M&A motives (Trautwein, 1990, 284)

<table>
<tr><td rowspan="5">Acquisition as rational choice</td><td rowspan="4">Acquisition benefits bidder's shareholders</td><td>Net gains through synergies</td><td>Efficiency theory</td></tr>
<tr><td>Wealth transfers from customers</td><td>Monopoly theory</td></tr>
<tr><td>Wealth transfers from target's shareholders</td><td>Raider theory</td></tr>
<tr><td>Net gains through private information</td><td>Valuation theory</td></tr>
<tr><td colspan="2">Acquisition benefits managers</td><td>Empire-building theory</td></tr>
<tr><td colspan="3">Acquisition as process oucome</td><td>Process theory</td></tr>
<tr><td colspan="3">Acquisition as macroeconomic phenomenon</td><td>Disturbance theory</td></tr>
</table>

As seen in the Table 1, the theories are efficiency theory, monopoly theory, raider theory, valuation theory, empire-building theory, process theory and disturbance theory. A common denominator in the first five theories is that they occur as a rational choice, whereas process theory occurs as process outcome and disturbance theory as macroeconomic phenomenon. A difference, on the other hand, in the first five theories is the gainer of acquisitions. The gainer is the acquiring firm's shareholders in the first four theories, whereas managers are the gainers in the fifth, empire-building theory. Furthermore, the first four theories are not identical either. In efficiency theory, net gains are achieved through synergies while in valuation theory they are achieved with the help of private information. Moreover, in monopoly theory wealth is transferred from customers whereas, in raider theory the wealth is transferred from acquired firm's shareholders.

From the seven theories two were left outside of the study. Raider theory is not widely recognized among scholars. In fact, Trautwein himself claim the theory to be incoherent and that it is lacking empirical evidence. Process theory, on the other hand, is left outside due to its difficulty to explain processes behind the theory. In addition, the theory can be seen rather undeveloped with little empirical evidence. Other five theories are discussed due to their plausibility and logical perspective. Efficiency theory, monopoly theory, valuation theory and empire-building theory are discussed in this Chapter due to their micro economical approach, whereas disturbance theory is discussed in Chapter 2.2. (Trautwein 1990, 288-289)

2.2.1 Efficiency theory

Efficiency theory is discussed firstly for a reason. Although, Trautwein highlights its importance in the framework of seven theories. It is also, perhaps, the most common and known motivation behind M&A. In addition, efficiency theory is clearly understandable in every day's business context. As an example, firms' executives often rationalize their actions based on efficiency. (Edson de Oliveira & Rotela 2013, 2626) However, the difference between defining the possible efficiency and actually achieving it, should be highlighted. According to Porter (1987, 54) companies often fail capturing already well-defined synergies. In fact, efficiency theory is all about synergies. Therefore, definition "synergy", should be understood. According to Edson de Oliveira & Rotela (2013, 2626), synergy, in business context, is additional value generated by the new entity of two firms enabling to achieve possibilities which were earlier impossible. The theory is divided into three sub-categories: financial synergies, operational synergies and managerial synergies.

Trautwein has further listed three ways to achieve financial synergies. The first way is to reduce the systematic risk by investing in different business areas as in conglomerate acquisitions. The second way is to increase the company size whereas the third way is to establish an internal capital market. The common goal with these three ways is to achieve lower cost of capital. In other words, a company can enjoy from lower interest rates and get the capital with better terms. (Rompotis 2015, 41) It is noteworthy that these ways have not succeeded without facing critique. According to Trautwein (1990, 284) in an environment of efficient capital markets financial synergies are hard to achieve. On the other hand, the literature focuses on the US firms where the capital market is the mostly advanced as efficiency. (Niskanen & Niskanen, 2007, 39) However, there are a plenty of markets which are not as efficient as US capital markets. Fei and Yun (2015, 53) have referred similarly to financial synergy in acquisition as attaining leverage effect, reducing the cost of capital and achieving tax-savings. Tax-savings, in particular, are often remarkable benefits in acquisitions. One attractive phenomenon among tax benefits is to use acquired firm’s accumulated taxable loss in acquiring firm’s own taxation. However, regulations and laws often tend to restrict this phenomenon. Other tax benefits may be related to changes in the tax scale and tax-free reserves. (Rompotis 2015, 40)

Operational synergies can be attained via combining separate units or sharing existing knowledge. These synergies result in lowering costs and better quality. However, the combining itself can be costly. Therefore, both pros and cons should be carefully considered. (Trautwein 1990, 285) Although operational synergies can be anything between cross-selling to rationalization of product portfolios, it is often linked to reduction of employees. (Lam et al. 2007, 1) As referring to different acquisition types discussed in Chapter 2.1, operational synergies have the strongest effect on horizontal acquisitions. (Rompotis 2015, 39) Managerial synergies, on the other hand, occur if the acquiring firm’s management have a capacity for accelerating the acquired firm’s performance better than the previous management. (Trautwein 1990, 285) Managerial synergies can be seen working on the other way around as within acqui-hiring phenomenon discussed in Chapter 2.1.

2.2.2 Monopoly and Valuation theory

The motive behind monopoly theory is to gain market power. Therefore, the objective is not necessarily to achieve a monopolistic position in the market as the theory's name refers but to achieve stronger marker share. (Trautwein 1990, 285-286) However, companies face several anti-trust regulations and competition laws if the proposed acquisition results in market dominance of unfair competition. (Czurak 1995, 1) In monopoly theory wealth transfers from customers. Therefore, acquisitions in this framework do not lower the prices nor enhance the selection of goods. (Peston 1987, 29) In fact, the prices tend to get higher. (Dow 2000, 2) Therefore, few companies justify a possible acquisition or merger based on the object of stronger market position in public. On account of this phenomenon the literature lacks evidence of monopolistic acquisitions. (Trautwein 1990, 286)

Synergistic advantages can be found both from related and unrelated acquisitions, i.e. financial synergies can be found from conglomerate acquisitions and operational synergies from horizontal acquisitions. However, according to Dow (2000, 1) monopoly theory applies for the most part in horizontal acquisitions. On the other hand, Trautwein (1990 286) states that monopoly theory can be behind conglomerate acquisitions as a motive as well. As an example, a company can use its profits from one market to reinforce its position in another market. Further, companies which are rivals with each other in multiple different markets can also establish a collusion in order to reduce competition. Lastly, conglomerate companies can hinder other companies' entrance to their markets.

According to valuation theory acquisitions occur because acquiring firm's managers have better information about acquired company than stock market. The managers either observe special advantages from the target firm's assets to acquiring company's own interest or the target company is only heavily undervalued. In case of the first instance, where the managers have private information, it is hard to evaluate the theory because the private information often remains as such. On the other hand, the both instances face criticism in the framework of efficient capital markets, where the stock prices are always properly valued. The other instance, where the target is only heavily undervalued is discussed more closely later due to its macroeconomic nature. Valuation theory, as difference to other theories, is only theory which recognizes the high uncertainty in remarkable decisions as in mergers or acquisitions. (Trautwein 1990 286-287) In addition, it should be noted that the theory works on the other way around as well. In some cases, a proposed merger or acquisition remains unsealed due to private information. After all, firms in acquisition are often rivals with each other. Therefore, the target firm could leave some valuable information outside of the negotiations preventing the possible acquisition. (Stähler 2014, 213) Lastly, it should be noted that leverage buy out-definition is strongly linked to this theory.

2.2.3 Empire building theory

The theory states that managers who participate in acquisitions or mergers promote their own interest rather than a firm's shareholders. In other words, managers can destroy shareholders' value in acquisitions instead of creating it. Therefore, agency problems are in the center of empire-building theory. Adam Smith states, in 1776, in the Wealth of Nations that the economy consists of rational actors who try to maximize their own benefit. Therefore, managers as actors in economy can be seen rationally orientated. Agency problem is created when managers act maximizing their interest at the expense of owners and as a consequence shareholder value is reduced. (Albanese et al. 1997, 609-610) Agency problem in an acquisition can be seen caused by managerial myopia or hubris, empire-building motivation and poorly working compensation system. (Fung et al. 2009, 388-289)

Gorton et al. have categorized two strategies why managers participate in acquisitions. Acquisitions and mergers occur either due to defensive or "positioning" reasons. Defensive acquisitions occur because managers want to remain their position in the management and therefore they acquirer other companies to prevent being acquired themselves. The presumption behind this phenomenon is that a larger firm size correlate negatively with likeliness to be acquired. However, while one company is practicing defensive merger strategy other companies become more exposed to be acquired. This leads to "eat or be eaten" scenario.

The other strategy is positioning. If a firm has succeeded well in previous acquisitions, it might become more attractive acquisition target as being more significant player than others. This encourages managers to take part in acquisitions. The similarity with these two strategies is managers' desire to promote their own interest. The difference, on the other hand, is whether shareholders' value is created or destroyed. The reason why managers succeed to promote both, their own interest and shareholders' in positioning strategy is that managers are as well shareholders as having a certain portion of ownership. When the managers have succeeded to turn the company to attractive target with the help of previous acquisitions and they are acquired themselves, they receive target premium as owners. (Gorton et al. 2009, 1293-1294) To compensate this view, Low (2007, 1) argue that managers' equity-based compensation is proven to diminish the conflict of interest with managers and shareholders.

This theory is not an exception when it comes to "working on the other way round"-dimension. Sometimes an acquisition does not occur due to managerial motives although the acquisition would create value to shareholders. Managers might prevent the acquisition in fear of their position. After an acquisition their role in the new company might reduce or they could even lose their jobs. (Gorton et al. 2009, 1292-1293) Moreover, the theory is not an exception either when it comes to critique. It has faced critique due to a lack of evidence. On other hand, few managers justify an acquisition by managerial objectives.

All in all, it can be stated that reduction of shareholders' value is the consequence of agency problem and it is caused by above mentioned factors. Yet it is undefined how, in fact, the shareholder value is destroyed. Trautwein (1990, 288) answers the question by stating that diminished shareholder value is resulted when managers overpay heavily the acquisitions.

2.3 Macro level reasons

This Chapter does not take a stand on the question why firms engage in mergers and acquisitions, the focus is on the environment where the deals occur. There is no single factor which defines the environment sufficiently, it is more like the sum of multiple different factors. In the framework of merger and acquisition literature, factors which effect on M&A activity, in particular, are macroeconomic environment, the level of technology and deregulation and political uncertainty. (Ricardo, 2000, 3, Hagendorff et al. 2007, 199-200)

2.3.1 M&A activity

M&A activity has increased both in volume and value from 1985 to 2019 as the first finding from the Figure. Second observation is the wavy movement in volume and value.

According to Yaghoubi et al. (2016, 147) M&A activity takes place in waves and the waves occur in different industries by different attributes through time. Third observation is that increase or decrease in volume and value does not necessarily go hand in hand. As it can be seen from the figure the value of M&A transactions dropped much more after the financial crisis in 2008 than the number of transactions.

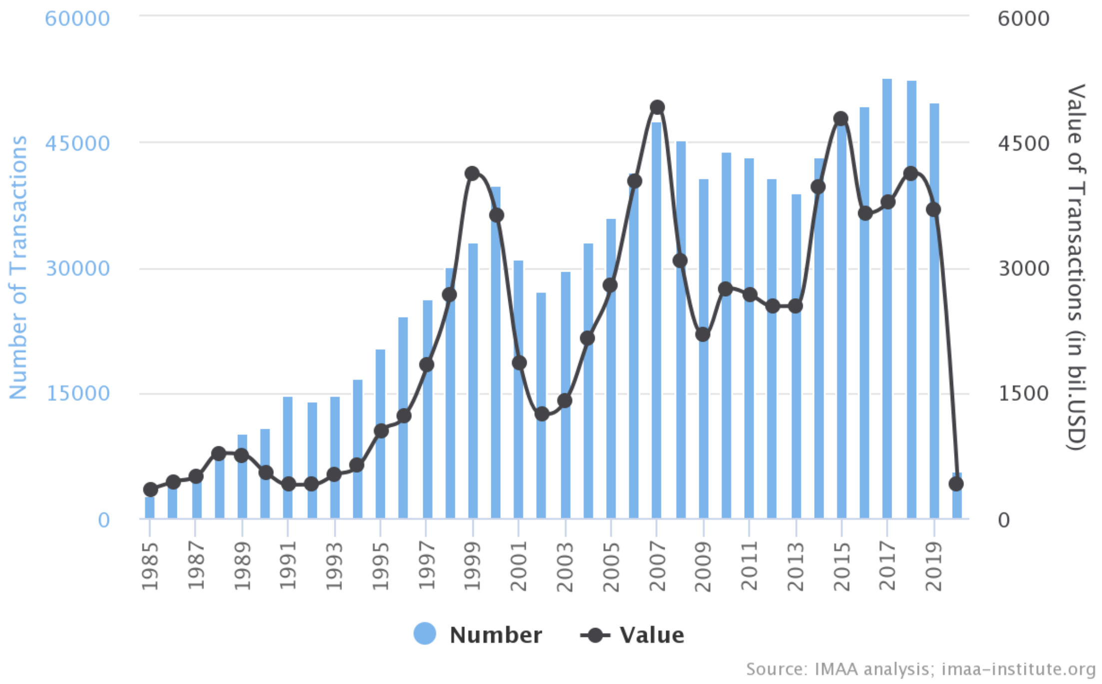

Figure 1 Mergers & Acquisitions Worldwide (Institute for Mergers, Acquisitions and Alliances)

There can be seen three clear peaks by value of transactions in the Figure 1, year 2000, year 2007 and year 2015. Yaghoubi et al. (2016, 149) have defined two first of them. Key attributes in the peak of the year 2000 were deregulation and stock payments. Stock payments, in particular, where common as valuations where high due to technological bubble. (Ljungqvist &Wilhelm 2003, 723) Moreover, M&A occurred between related business within major industries such as real estates and metal mining. Second peak in 2007 was attributed by cash payments and friendly negotiations. In addition, whereas first peak occurred in related business, the second peak was dominated by cross-border acquisitions which are mainly conglomerate as stated in Chapter 2.1. Main industries in the second peak were banking and telecom. The last peak in 2017 is lacking academic literature due to its newness. Nonetheless, it can be stated that interest rates were historically low and stock market was relatively high which are both seen to boost M&A activity. (federalreserve.gov, Economic Research & Data, Yagil 1996, 184, Choi & Jeon, 2011, 235)

2.3.2 Macroeconomic factors

After 2008's financial crisis the macroeconomic environment has changed dramatically. Both US and European economies have been struggling with low GDP growth rates. Neither US nor the European biggest economies have been able to achieve as good GDP growth rates as before the crisis. (Worldbank) This period of stagnation has forced both continents central banks to drop interest rates at historically low level. (European Central Bank, Federal Reserve) Low interest rates combined with high stock prices create an interesting environment to mergers and acquisitions.

Interest rates effect on the M&A activity as a double-edged sword. Yagil (1996, 184) argue that an increase in interest rates affects positively on M&A activity because the cost of financing an investment as a way of organic growth increases. Moreover, Jurgis Oniunas, chairman of global advisory network IMAP, argue similarly that low interest rates may prevent merger and acquisition deals to occur. He takes into consideration target's standpoint stating that targets won't sell their businesses because there is no possibility to get higher yield to their capital due to low interest rates. On the other hand, acquisitions are financed in large part by debt. Therefore, the cost of capital increases as interest rates increases and a negative correlation between an increase in interest rates and M&A activity is found. (Ricardo, 2000, 3) Debt is a common among mergers and acquisitions due to its advantages in taxation. Interest are deductible in taxation whereas dividends are not. (Clements et al. 1992, 8-9) All in all, the consensus among scholars regards the sword, at any rate, sharper from the negative correlation point of view. (e.g. Stephen, 1995, 28, Choi & Jeon, 2011, 240, Hogan et al. 2015, 61)

Whereas there is a negative correlation between high interest rates and M&A activity, the correlation is positive when it comes to high stock market valuations and deal activity. (Choi & Jeon, 2011, 235) As in interest rates, the explanatory factor is the method of payment in acquisitions. Shleifer and Vishny (2001, 20) prove that a significant part of all mergers and acquisitions are financed with own stocks. Further, they state that stocks rose above 70 per cent as a method of payment in the 1990s. High valuations in stock markets signify that when acquiring firms stock value more they as well get more from the target. On the other hand, high stock valuations tend to make targets more valuable as well and, therefore, diminish the M&A activity. (Dolbeck 2006, 1) Nonetheless, acquirers tend to be relatively more highly valued than the targets, even if both would belong to the same industry. (Shleifer and Vishny, 2001, 22) Stock market valuations are strongly linked to Trautwein's valuation theory discussed in Chapter 2.2.2. The difference is that Trautwein observes valuations as micro level phenomenon where managers obsess private information about targets, and it does not take a stand on macro level M&A activity.

As cross-border acquisitions have become much more common in the framework of mergers and acquisitions, the significance of currency movements should be considered. (Zou 2012,1, Erel et al. 2010, 1) As the value of currency in one country is increased relatively to other country, the other county's firms are more likely to be targets of acquisitions from the country with the stronger currency. (Erel et al. 2010, 2) As a demonstrative example, if US dollar is appreciated 10% higher than euro, a potential acquisition between companies from US and Germany would be 10% more expensive from Germany based company's point of view. Another factor in macroeconomics which has an impact on M&A activity is GDP growth rate. GDP growth rate measures economic growth from one country's perspective. The consensus among scholars argue that there is a positive correlation between the activity and growth in GDP. (e.g. Choi & Jeon, 2011, 239, Humberto 2010, 13)

Lastly it should be noted that macroeconomic factors effect on M&A ambiguously, in other words these factors do not have impact merely on the deal activity. In 2008 and 2009, right after financial crisis, strategic alternatives, such as joint ventures, strategic alliances, licensing and franchising, increased their role as gradual approach to partnerships like ever before due to changed macroeconomic environment with a lack of access to capital markets. (Sherman, 2010, 281-282) In addition to other strategic alternatives macroeconomic factors have an impact on the method of payment as well as stated above. Furthermore, one should comprehend that as a group mergers and acquisitions are seen rather homogeneous one than heterogeneous one. This statement refers to different types of acquisitions. As the motivations behind acquisitions are different in different types of acquisitions so are the impacts by macroeconomic factors. Whereas horizontal and vertical acquisitions occur mainly due to specific corporate objectives, conglomerate acquisitions are often linked to financial motivations. Therefore, conglomerate acquisitions are more strongly affected by macroeconomic factors, such as interest rates, than horizontal and vertical acquisitions. (Yagil 1996, 183)

2.3.3 Other macro level factors

All factors that are linked to M&A activity are not macro economical. The level of deregulation and technology and political uncertainty have also impacts on the activity from macro level. Political uncertainty, in particular, has not received as much academic attention as other macro level reasons, not to mention all the micro level factors.

According to Yaghoubi et al. (2016, 154) deregulation can effect on mergers and acquisitions by two ways. Firstly, deregulation can create new investment opportunities to industry and therefore boost M&A activity. Secondly, deregulation can remove barriers from consolidation. Hagendorff et al. (2007,199-200) argue similarly that deregulation has a positive effect on M&A activity. They prove that in banking sector, which is heavily regulated due to its position in society, deregulation has improved deal activity. On the other hand, regulation can drive companies into mergers and acquisitions as well. For instance, Nordea, the biggest bank in Nordic countries, had motivations to merge with other European bank due to possibility of harder regulation in its former home country Sweden. (yle.fi/yrityskaupat) Nonetheless, there is no academic support stating regulation would enhance deal activity, the consensus among scholars is with the deregulation.

Increased level of technology, on the other hand, effects on M&A activity positively by two ways. Firstly, increased technology, like deregulation, creates new business opportunities to companies and can therefore boost M&A activity. Secondly, new technology tends to be expensive and therefore fixed costs increases. As a result, this leads to a situation where companies have temptations to merge with each other in order to share the increased fixed costs. (Bhalla, 2014, 130) Furthermore, Yaghoubi et al. (2016, 154) take a deeper stand how new technology effects on deal activity. They argue that those companies who are inflexible become targets for acquisitions by agile companies who are capable to embed new technology to their strategy.

Decisions to engage in mergers and acquisitions are made by human beings. In a result, uncertainty of any kind is toxic to M&A activity. Another macro level factor which effects on the deal activity is political situation, in particular, political uncertainty. As seen in the Figure 1, value for 2016 M&A activity is not as high as in year 2015. According to Financial Times, one reason of decreased deal activity is political uncertainty. Two major political shocks occurred in 2016, UK’s withdrawal from the European Union and Donald Trump’s victory in US presidential elections. In addition, populist parties in

France, Germany and Italy have caused uncertainty with elections and referendums. Many chief executives have, probably, postponed their plans for M&A. There are several concrete and major examples about the negative effects on the deal activity by political uncertainty. One of them is Deutsche Börse's proposed merger with London Stock Exchange, which is struggling due to Brexit. On the other hand, some positive effects can be found as well when uncertainty is creating opportunities. For instance, China, where M&A activity is increased compared to year 2015, is taking an advantage of uncertainty in Europe and especially from weak pound. (ft.com/Mergers&Acquisitions)

3 LITERATURE REVIEW

Scholars started to study takeover predictability in the 1970s. The gradual increase among academics to research the topic is believed to be linked with well researched area, corporate default prediction. For academics to start studying a new phenomenon, corporate takeover prediction, was rather smooth transition as methodologies between corporate default prediction and corporate takeover prediction are strongly similar, both study binary results and are based on similar financial data. (Tian 2012, 1)

When takeover prediction as a field of study started to raise interest, academics wrote papers with extremely high accuracy rates from 75% to 95% and the rates were commonly justified and unchallenged. (Powel, 2001, 994) However, the field of study faced a paradigm shift when Palepu published his paper in 1986. Palepu discovered that high accuracy rates in prior studies were caused by statistical flaws. According to Palepu (1986, 31) the earlier acquisition prediction studies incorporate three principal methodological flaws which make the reported prediction accuracies unreliable. First, the use of non-random equal share samples in the model estimation results in overstating the model´s ability to predict acquisition targets as the model parameters and accuracy rates are biased and inconsistent. Second, the use of equal share samples in prediction tests leads to error rate estimates that fail to represent to model´s predictive ability in the whole population. Third, the use of arbitrary cutoff values in prediction tests is a common methodological issue in the earlier takeover prediction studies. According to Palepu (1986, 12) the earlier takeover prediction studies lack predefined decision context for cut-off values, and use arbitrary cut-off probabilities, usually 0.5. The usual cut-off level, 0.5, should not be a given level, but the level should be rather mathematically defined. The lack of predefined and specified decision context for cut-off values makes the reported prediction accuracies difficult to interpret.

The first two methodological issues are linked to unbalanced sample construction with targets and non-targets. Targets represent only a fraction of the whole population and, therefore, drawing a sample with equal number of targets and non-targets is not based on random sampling as a firm’s probability of being selected into equal share sample is a function of its acquisition status. A vast majority of takeover prediction models published prior to Palepu’s paper were employing equal share samples, but still employing estimators which assume random sampling. (Palepu, 1986, 6-7) Cosslet (1981, 96) finds this method to cause bias of 30% or more, which underline the severity of the problem. Palepu points out that there are econometric justifications to equal share samples as well as ''information content'' is richer relatively to randomly selected samples, the problem is only the random sampling assumption behind estimators. According to Palepu (1986, 10) there is no econometric justification of equal share samples of targets and non-targets in the prediction phase, unlike in the estimation phase. Therefore, Palepu argues that the prediction sample should resemble the whole population as closely as possible.

Palepu employs binary logit regression with a sample of 163 companies, which were targets of acquisition during the period 1971-1979 and 256 companies which were not targets of acquisition as of 1979 as a control sample. Palepu finds his model to be statistically significant with low explanatory power. When the model was tested on a group of 1117 companies, the model correctly classifies 24/30 (80%) actual targets and 486 of the 1087 (45%) actual non-targets. Thus, model is successful to predict actual targets but lacks power to predict actual non-targets, which leads to average overall result. To emphasize Palepu´s results, Chueh (2013) points out that the high accuracy rates prior to Palepu´s paper have not been achieved since in the academic literature.

3.1 Development of prediction methodologies

History of M&A predictability lies in corporate default prediction. In the early 1970s academics started to study M&A predictability since the methodologies between corporate default prediction and takeover prediction are rather similar as both predictions study binary results. Since 1970s, methodological processes such as sample construction techniques have sharpened and many different statistical models have been introduced to academics studying takeover prediction.

A vast majority of the statistical models developed for takeover prediction are based on either multiple discriminant analyses (MDA) (e.g. Simkowitz and Monroe, 1971, Stevens, 1973, Barnes, 1990) or logistic regression models (e.g. Palepu, 1986, Clayton & Fields, 1991, Ambrose & Megginson, 1992, Powell, 2004). In addition, many variations of the above-mentioned models such as probit models (e.g. Harris, Stewart, Guilkey & Carleton, 1982) and conditional logistic regression models (e.g. Tsagaknos, Georgopoulos & Siripoulos, 2006) have been employed in takeover prediction literature. Probit model is otherwise identical to logistic model but probit model is based on standard normal distribution, whereas logistic model is based on logistic distribution. Conditional logistic model is identical to simple logistic model, the only difference being conditional logistic model's capability to employ conditional matching. Within takeover prediction literature the matching is generally based on different years or different industries in order to exclude possible variations in macroeconomic environment and to match only targets and non-targets within particular industry. In addition to statistical models, academics have employed many mathematical models as well within takeover prediction literature. For instance, machine learning, artificial neural networks, recursive portioning and rough set models have all been used to predict acquisition targets (Chueh, p. 158, 2013).

Simkowitz and Monroe (1971) were among the first researchers to predict acquisition targets based on financial data. They succeeded to construct a MDA-model with 63.20 % prediction accuracy. Albeit the model included severe methodological issues mainly linked to data sampling techniques, the study created fundamental base for takeover prediction research with financial data. The fundamental base strengthened significantly when Palepu (1986) published the mostly cited paper in the takeover prediction history. Palepu was among the first scholars to employ logistic regression model and it can be stated that logistic regression model has been the mostly used model in the takeover prediction literature ever since. Logistic regression's biggest advantage against other models is its capability to classify targets and non-targets as well as its capability to give a probability of a such event.

3.2 Prediction variables and hypothesis in previous literature

Prediction parameters can be classified into three groups; firm specific factors, industry specific factors and macroeconomic factors. Firm specific factors examine targets and non-targets from micro level whereas macroeconomic factors and industry specific factors look at firms from much broader perspective. A vast majority of previous literature has been studied firm specific parameters but industry specific as well as macroeconomic parameters are mainly left outside of previous studies. However, it can be argued that industry specific factors and macroeconomic conditions correlate strongly with the overall M&A activity. Therefore, parameters implied from these two factors arguably affect the probabilities of M&A target prediction.

As the prediction model is only as good as the variables it is based on, it is crucial to fully comprehend all the variables and their relationship with each other to prevent multicollinearity. Moreover, it is important to pre-specify all the parameters included in the prediction model in order the model to be methodically clean. Palepu (1986, 16) finds out that many previous academics executed their studies other way round as they first pooled large number of variables and step by step reduced all the statistically insignificant variables from their studies (e.g. Simkowitz & Monroe, 1971).

The previous literature has used a large number of different and different kind of parameters. Therefore, many of them are left outside of this Chapter. This Chapter focuses on Palepu's (1986) six hypothesis as they are the base hypothesis for mainly all studies published after Palepu. These six hypotheses can be categorized into firm specific and industry specific variables.

3.2.1 Firm specific variables

Size hypothesis is based on assumed negative correlation between firm size and takeover likelihood. Palepu (1986, 18) justifies the hypothesis with size related transaction costs related to acquisition. For instance, bigger companies can defend themselves much better from a hostile takeover than smaller companies can. In addition, Palepu states that integration costs rise with the firm size and thus make the potential target less attractive to acquiring firms. Palepu tests this hypothesis with firm's net book assets whereas later published studies such as Barnes (1999), have used number of employees, revenue and equity value as size parameters.

Undervaluation hypothesis, which is in fact combination of market-to-book hypothesis and price-earnings hypothesis. According to market-to-book hypothesis, firms with lower market-to-book ratios are more likely to be targets because they are undervalued against their higher market-to-book counterparts. Thus, the market-to-book ratio is included as a variable in Palepu's hypothesis. Moreover, price-earnings hypothesis states that firms with low P/E ratios are more likely targets of an acquisition than firms with high P/E ratios. The rationale behind this hypothesis is the belief that companies with high P/E ratios tend to buy companies with low P/E ratios because of immediate capital gains as the acquiring companies believe that stock market values the new entity after the acquisition with the old entity's, acquiring firm's, P/E ratios.

Inefficient management hypothesis claims firms with inefficient management to be more likely targets of an acquisition than firms with efficient management. This hypothesis is strongly linked to finance theory and it sees acquisitions as a mechanism to change the inefficient management, which has failed to maximize the shareholder value. Hostile takeovers are often related to inefficient management, thus they can be seen as a relevant example of the hypothesis. Palepu uses excess returns of the firm stock as a proxy of inefficient management. However, a vast majority of later studies have used profit margins, asset turnover, ROE and sales growth as proxies.

Growth-resource mismatch hypothesis states that firms with imbalance in their growth and financial resources are more likely targets than firms with matching growth and financial resources. Palepu (p. 23, 1986) finds evidence to back the hypothesis as growth-resource mismatch as a variable contains statistical significance and positive relationship with takeover likelihood in all four models of his paper. Corporate finance literature has mainly focused to study resource-rich firms with low growth rates rather than resource-poor firms with high growth rates. However, both above are linked to higher probability to become targets of an acquisition. Growth-resource mismatch hypothesis can be tested by denoting a dummy variable. Dummy variable gets value 1 if target is either high growth and low resource or low growth and high resource.

The previous literature is mainly based on Palepu's six hypothesis. However, many scholars have added more variables into their studies. For instance, Cudd & Duggal (2000), Powell (2004) and Brar, Giamouridis and Liodakis, (2009) have used liquidity as a variable in their studies. All of these studies show liquidity to be significantly lower with targets than non-targets as lower liquidity means lower financial power. The variable can be tested, for instance, comparing cash to total assets or comparing current assets to current liabilities. Furthermore, Cremers, Nair and John (2009, p. 1421) find leverage to be statistically significant variable. They find leverage of a firm to be positively correlated with the likelihood of becoming a target. Leverage can be tested by comparing total debt to equity or by comparing total debt to assets.

3.2.2 Industry variables

As the hypothesis above look at targets from firms' inner perspective, *Industry disturbance hypothesis* assumes that firms within an industry, which are subjected to ´´economic disturbances´´ are more likely to be acquisition targets. According to Gort (1969) changes in technology, industry structure and regulatory environment are all forces that accelerates consolidation across industries. Based on Gort's findings, Palepu (1986) incorporates a dummy variable into his model. The dummy variable is set to value 1 if within an industry has been at least one acquisition during the year before the observation. Palepu

(1986), among many other academics, use four-digit SIC-code in order to classify industries.

3.2.3 Macroeconomic variables

Macroeconomic variables are almost categorically left outside of study in takeover prediction literature. Many academics such as Yagil (1996), Ricardo (2000), Hagendorff et al. (2007) and Yaghoubi (2016) have studied and proved the positive relationship with multiple macroeconomic factors and M&A activity. For instance, the effects of GDP, interest rates, exchange rates, central bank monetary policy, government fiscal policy and current position in the macroeconomic cycle have been studied on M&A activity level, but these variables lack existence in takeover prediction models. According to author's best knowledge, only Brar, Giamouridis & Liodakis (2009) have incorporated macro factor in their takeover prediction model. They used European broad market index developed by Citygroup in order to denote a dummy variable to indicate either positive or negative macroeconomic situation. Brar, Giamouridis & Liodakis did not find the macro dummy to be statistically significant, which might have decreased the willingness to incorporate macroeconomic variables in later published takeover prediction studies.

Table 2 Literature Review

Author(s)	Year published	Geographic region	Sample period	Methodology	Significant variables	Data T=Target ; NT= Non-Target	Prediction power
Simkowitz and Monroe	1971	USA	1968	Multiple discriminant analysis	Market cap, P/E, dividend payout ratio, equity growth	23 T:s and 15 NT:s	63.20 %
Stevens	1973	USA	1966-1970	Multiple discriminant analysis	Ebit/Sales, Sales/TA, NWC/TA	40 T:s and 40 NT:s	70.00 %
Harris,Steart, Guilkey & Carleton	1982	USA	1974-1977	Probit model	N/A	106 T:s and 1200 NT:s	N/A
Palepu	1986	USA	1971-1980	Logistic regression	Growth resource dummy, Total Assets	163 T:s and 256 NT:s	45.60 %
Barnes	1990	UK	1986-1987	Multiple discriminant analysis	N/A	90 T:s and 90 NT:s	74.30 %
Ambrose & Megginson	1992	USA	1981-1986	Logistic regression	Change in shareholding, Voting rights, FA/TA	169 T:s and 267 NT:s	N/A
Powell	1997	UK	1984-1991	Logistic regression	Liquidity, Size, Free Cash Flow	411 T:s and 532 NT:s	N/A
Barnes	1999	UK	1991-1993	Logistic regression	Profitability, Sales growth, Equity Value	82 T:s and 82 NT:s	98.60 %
Cudd & Duggal	2000	USA	1987-1991	Logistic regression	Size, ROE, Sales growth, Leverage Liqvidity, Industry disturbance	108 T:s and 235 NT:s	76.10 %
Powell	2004	UK	1986-1995	Logistic regression	Liqvidity, Size, Industry disturbance	471 T:s and 9,420 NT:s	90.00 %
Tsagaknos, Georgopoulos & Siripoulos	2006	Greece	1995-2001	Conditional Logistic regression	change in shareholding, voting rights, FA/TA	56 T:s and 305 NT:s	93.20 %

4 DATA AND METHODOLOGY

4.1 Hypotheses

As nearly all studies published after Palepu's (1986) celebrated paper, this thesis bases its hypotheses on Palepu's six hypotheses that are related to firm size, inefficient management, market-to-book hypothesis, price-earnings hypothesis, growth-resource mismatch and industry disturbance hypothesis. This thesis' only modification to Palepu's six hypothesis is combination of market-to-book hypothesis and price-earnings hypothesis as they both are strongly linked to firm's valuation and, therefore, the combined hypothesis is named as valuation hypothesis. In addition to these hypotheses, this thesis incorporates free cash flows, indebtedness, liquidity, investment behavior and macroeconomic environment as hypotheses into the logistic regression model. These ten hypotheses and variables implied by them are discussed below and an overview of the hypotheses, variable calculations and their expected implications to the takeover probability are presented in Table 3.

Hypothesis 1: Size – Firms' size and the probability to be taken over are negatively correlated.

As the firm size increases, the number of potential bidders decreases. In addition, larger size indicates larger transaction costs e.g. integration and due diligence costs. As the vast majority of the existing body of research, this thesis uses total sales and total assets as proxies for size hypothesis. In addition to these two parameters, the previous literature has used market capitalization as a proxy to describe firm's size. This thesis uses, concurrently with market capitalization, enterprise value as a proxy for the first hypothesis. Enterprise value has better capability to take target's debt and cash reserves into account, which are important aspects in every acquisition. Total sales, total assets, market capitalization and enterprise value are measured by the natural logarithm of them as large standard deviation of absolute numbers might decrease the explanatory power of the conditional logistic regression model.

Hypothesis 2: Valuation – Firms' valuation and the probability to be taken over are positively correlated.

The existing literature has mainly used market-to-book ratios (P/B), price-earnings (P/E) and price-sales ratios (P/S) to define whether the company is undervalued or not. This thesis sees these three multiples as good proxies when it comes to company valuation and they are therefore all selected as proxies to the second hypothesis. However, EV/EBITDA-multiple, which is perhaps the most used valuation multiple in the context of M&A, is added as a proxy as well due to its industry-wide utilization and multiple's capability to incorporate companies' debt and cash reserves into valuation. Palepu's (1986) as well as many other researchers', e.g Barnes (1999, 290), hypotheses assume negative correlation between firm valuation and the probability to become a takeover target. This hypothesis is based on an assumption that acquirers seek ´´cheap assets´´ to buy. This thesis, conversely, assumes positive relationship with takeover probability and firm valuation. This thesis assumes acquirers to seek targets with certain competitive advantages, strong market positions or others strategic fits, which are, in turn, reflected to targets' valuation.

Hypothesis 3: Inefficient management – Firms with inefficient management are more likely to become takeover targets.

Existing literature has deep consensus that firms with efficient management are less likely to become takeover targets. Finance theory states that firms' main objective is to produce shareholder value to its owners. Based on this statement, return on equity (ROE) is selected as a proxy to hypothesis 1. Secondly, companies tend to seek growth and management which fails to grow its revenues can be seen as inefficient. Therefore, sales growth is used as a second proxy to first hypothesis. Thirdly, management who increases firm's top line but decreases the firm's bottom line can be seen, as well, as inefficient. Thus, EBITDA-margin, profit-margin and asset turnover are selected as the last proxies for the first hypothesis.

Hypothesis 3: Growth-financial resource mismatch – Firms with imbalance between growth and financial resources are more likely to become takeover targets.

According to Palepu (1986, 17) two types of firms are more likely to become takeover targets: low-growth, resource-rich firms and high-growth, resource-poor firms. Thus, the third hypothesis can be tested by denoting a dummy variable. Dummy variable gets value 1 if target is either high growth and low resource or low growth and high resource.

In more detail, dummy variable gets value 1 if there is either low growth + high liquidity + low leverage or high growth + low liquidity + high leverage. In this thesis, growth is explained by one-year sales growth whereas financial resources are explained by liquidity (cash-to-total assets) and leverage variables, which compositions are explained in more detail in the Appendix 1.

Hypothesis 4: Industry disturbance – Firms within an industry that is affected by ′economic disturbance′ are more likely to be taken over.

Palepu (1986, 18) argues that acquisitions cluster by industry. Therefore, recent history of M&A activity in one industry is assumed to indicate future M&A activity in that particular industry. This thesis, as many previous studies, uses SIC industry codes in order to denote a dummy variable. The dummy variable gets a value one if at least one transaction was identified with the same SIC code one year before the observation.

Hypothesis 5: Cash Flows – Firms' with extensive cash flows are more likely to become takeover targets.

This hypothesis is based on Jensen Free Cash Flow hypothesis (1986). Jensen states that a firm is more likely to be taken over if it has large free cash flows which are not returned to shareholders. Thus, M&A is seen as a tool to prevent target's management invest free cash flows in projects with questionable or negative net present value. This thesis uses operating cash flow margin as a proxy due to its strong explanatory power of free cash flows.

Hypothesis 6: Indebtedness – Firms' indebtedness and the probability to be taken over are positively correlated.

Brar, Giamouridis & Liodakis (2009) state takeover targets to have higher indebtedness levels than non-targets. Therefore, positive relationship between firm's indebtedness and firm's likelihood of being taken over is assumed. In this thesis, indebtedness is measured by leverage and gearing ratios. Leverage ratio is measured as 'Total Debt / Total Assets' and gearing ratio is measured as '(Total debt – Cash & marketable securities) /Common Shareholder Equity'.

Hypothesis 7: Liquidity – Firms' liquidity and the probability to be taken over are negatively correlated.

Hypothesis 6 focuses on the overall financial situation of a firm, but it might not explain challenges what firms face on a shorter-term. Therefore, short-term financial capacity i.e. firm's liquidity is incorporated as a hypothesis to this study. Based on previous studies (e.g. Brar, Giamouridis & Liodakis, 2009), liquidity is assumed to be in negative relationship with takeover probability. Current ratio and a cash-to-total assets ratio are used as proxies for firm's liquidity.

Hypothesis 8: Investment behavior – Firms with high investments and the probability to be taken over are positively correlated.

Firms which take concrete steps in order to implement predefined strategies by investing in the future are seen more attractive takeover targets than firms which do not engage with such future-orientated investment activities. Thus, capital expenditures to sales ratio is used as a proxy for the eighth hypothesis.

Hypothesis 10: Macroeconomic condition – Firms operating under a favorable macroeconomic environment are more likely to be taken over.

Many academics (e.g. Ricardo, 2000, Hagendorff et al. 2007) have found positive relationship between macroeconomic environment and M&A activity. This thesis studies how macroeconomic environment affect the likelihood to become takeover target on a firm level. A dummy variable is denoted to every firm based on the year and country of the observation describing macroeconomic condition of given time and country. Gross domestic product (GDP) is selected as an indicator of macroeconomic condition due to its simplicity and high explanatory power. Many other indicators were considered as well, for instance consumers' confidence indices, interest rate levels and financial condition indices, but severe multicollinearity was found among all indicators. The dummy variable gets value of 1 if the growth of gross domestic product in a given year and country is positive and value of 0 if the growth is negative. GDP growth rates were retrieved from World bank.

Table 3 Overview of hypotheses and variable calculations

Expected sign column implicates either expected positive or expected negative relationship with variables linked to the hypotheses and takeover probability. Plus sign indicates a positive relationship with the variables and the takeover likelihood, whereas minus sign indicates a negative relationship with the variables and takeover likelihood.

Hypotheses & Variables	*Calculations*	*Expected sign*
Size		
Market capitalization (MEUR)	No calculation applied	-
Enterprise value (MEUR)	No calculation applied	-
Total assets (MEUR)	No calculation applied	-
Net sales (MEUR)	No calculation applied	-
Valuation		
P/E	Equity market value / Net Income	+
P/B	Equity market value / Book value	+
P/S	Equity market value / Total Sales	+
EV/EBITDA	Enterprise value / EBITDA	+
Inefficient management		
1-year sales growth	$(Sales^{t1}-Sales^{t0}) / Sales^{t0}$	-
ROE	Net Income / Common Equity	-
EBITDA-margin	EBITDA / Sales	-
Profit-margin	Net Income / Sales	-
Asset turnover	Sales / Total Assets	-
Cash flow		
Operating cash flow -margin	Operating cash flow / Sales	+
GR mismatch		
Dummy	Dummy=1 if GDP growth has a positive value in a given year, otherwise 0	+
Industry disturbance		
Dummy	Dummy=1 if M&A activity in given industry previous year, otherwise 0	+
Indebtedness		
Leverage	Total debt / Total Assets	+
Gearing	(Total debt – Cash) / Common Equity	+
Investment behavior		
Capex-margin	Capital expenditures / Sales	+
Liquidity		
Cash/Total assets	Cash / Total Assets	-
Current ratio	Current Assets / Current Liabilities	-
Macro		
GDP-dummy	Dummy=1 if GDP growth has a positive value in a given year, otherwise 0	+

4.2 Data

Due to methodological requirements of logistic regression data used in this study is divided into different samples and sections. First, the data is divided into target sample and non-target sample. Companies who become targets of an acquisition are classified as targets and companies who are not targets of an acquisition are classified as non-targets. Second, the data used in this study is divided into estimation section and prediction section based on the year of the observation. Estimation section consists all the observations from January 2001 to December 2014, whereas prediction section consists all the observations from January 2015 to December 2018. The data is retrieved from two different data bases. SDC Platinum (Securities Data Company) database is used to retrieve raw financial data from targets and DataStream database is used to retrieve raw financial data from non-targets.

Table 4 Data screening criteria

All the criteria presented below are applied with target sample and non-target sample gathering and criteria presented in grey area are applied only with target sample gathering.

Screening criteria	
Time Frame	01.01.2001-31.12.2018
Location	Finland, Sweden, Norway, Denmark, Germany, France
Ownership type	Publicly listed
Sector	Financial sector excluded
Transaction status	Completed
Transaction value	>50 MUSD
Transaction term	Percent owned 0-49, percent sought 50-100

Similar criteria for both data samples, targets and non-targets, are used when preliminary raw data is retrieved. Firstly, the time frame for both the samples is from January 2001 to December 2018. Secondly, all the companies in both data samples must be located in the following countries; Finland, Sweden, Norway, Denmark, Germany and France. Thirdly, both targets and non-targets must be listed companies. Whether acquiring companies are listed or unlisted is seen irrelevant to this study. Fourthly, financial sector is totally excluded from both data samples as in many corresponding studies. This is conducted by excluding all the SIC-codes (Standard Industrial Classification) from 6000 to 6999 as screening the preliminary data.

Certain additional criteria for target sample is employed. All the transactions must be completed, not only announced. All the transactions below 50 million USD enterprise value are excluded to keep the data reliable and relevant. Furthermore, the acquiring firm can have only owned maximum 49% of the target's shares in advance and must have sought 50%-100% of the target's shares afterwards.

A significant number of observations is dropped after retrieving the preliminary raw data as many observations lacked financial data to the needed 22 variables.1 After employed screening criteria and dropped observations, total number of observations is eliminated to 17 476 including 702 targets and 16 774 non-targets as well as 13 797 estimation sample observations and 3 681 prediction sample observations as seen in the Table 5.

The data is gathered for targets and non-targets from the end of the fiscal year prior to the observation year. For example, a company was acquired in 2010, which is the observation year and all the variables are measured using 2009 year end data. Palepu (1986) and Powell (2004), among other scholars, have used similar timeframe in data gathering. There are both advantages and disadvantages related to this kind of data gathering. The advantage is that the data is relevant and up-to-date, but this method has its methodological flaws as well. The data might not have been publicly available with respect to takeovers occurred during first months of a year as companies tend to publish their financial statements during spring. Powell (2004, 26) acknowledges the bias, but still constructs the takeover prediction models with year end data preceding the observation year. Powell handles the bias only when he constructs portfolios trying to generate abnormal returns by simply ignoring the abnormal return of the first three months generated by the models as most of the companies have published their financial statements within the first three months of the year. In addition, this bias only concerns the deals occurred within the first months of the year and three out of four financial statements from the year preceding the observation year were certainly published. Therefore, the above described data gathering process is justified. Nonetheless, it should be noted that some scholars who have studied abnormal returns of takeover prediction models, such as Danbolt et al. (2016), have lagged independent variables in order to mitigate the look-ahead bias.

[1] Elimination processes can be seen in more detail in Appenxix 1.

Table 5 Division of observations

Division of observations			
	Estimation Sample	Prediction Sample	***Total***
Target Sample	577	125	*702*
Non-Target Sample	13 218	3 556	*16 774*
Total	*13 797*	*3 681*	17 476

4.2.1 Targets

The data for target sample is retrieved from SDC database. The screen yielded 702 transactions in Finland, Sweden, Norway, Denmark, Germany and France from 01.01.2001 to 31.12.2018. The target sample is further divided into two sections. All the 577 transactions from 01.01.2001 to 31.12.2014 belong to estimation section, whereas all 125 transactions from 01.01.2015 to 31.12.2018 belong to prediction section. All the 702 transactions, i.e. observations in the target sample represents 4% of the whole data set, i.e. estimation and prediction sections combined.

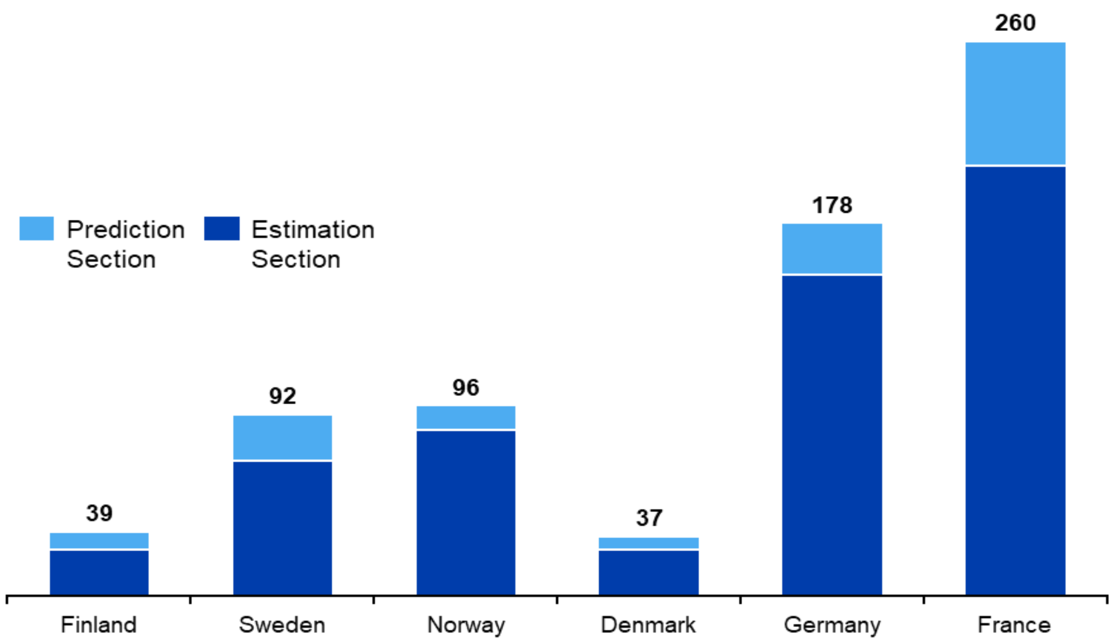

Figure 2 Target Sample by country

As seen from the Figure 2, France and Germany represent the vast majority of transactions in both estimation and prediction sections, whereas the number of transactions in Denmark and Finland is relatively low in both sections. Moreover, it can be seen from the Figure 3 that the number of transactions per year is on average higher and less volatile prior the hit of financial crisis in September 2008. In addition to financial crisis, the European debt crisis further explains the lower and more volatile deal volume after 2008.

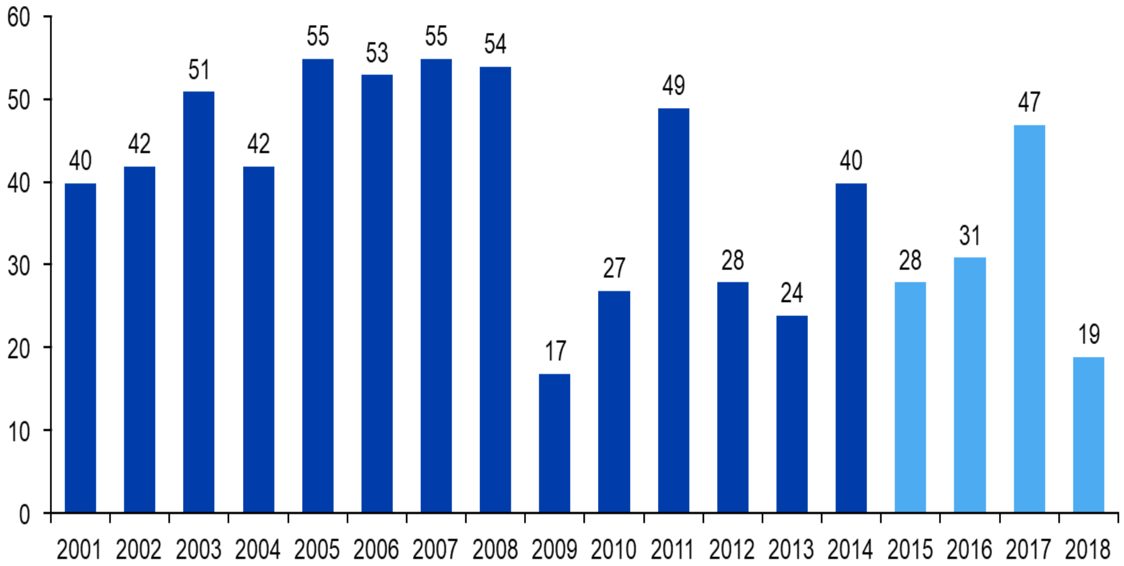

Figure 3 Target Sample by years

Table 6 provides descriptive statistics for target sample's 577 observations in estimation section. Descriptive statistics include mean, standard deviation, minimum and maximum values for all variables in the target sample's estimation section.

Table 6 Descriptive Statistics Estimation Section's Targets

Descriptive Statistics Estimation Section's Targets					
Variables	*Obs*	*Mean*	*St.dev*	*Min*	*Max*
Size					
Market capitalization (MEUR)	577	1,694.3	5,743.5	10.000	81,800.0
Enterprise value (MEUR)	577	3,286.9	20,000.0	45.008	444,000.0
Total assets (MEUR)	577	2,185.6	8,784.2	1.600	163,000.0
Net sales (MEUR)	577	1,870.2	9,269.5	0.885	203,000.0
Valuation					
P/E	577	24.7171	65.9732	-150	400
P/B	577	3.4048	5.3809	0	50
P/S	577	2.3527	7.1092	0.0098	100
EV/EBITDA	577	13.4119	21.8739	-100	100
Inefficient management					
1-year sales growth	577	0.2611	1.4513	-0.5624	24.5433

ROE	577	0.0715	0.4455	-5	4.4124
EBITDA-margin	577	0.0924	0.4737	-5	3.1388
Profit-margin	577	0.0272	0. 2118	-1	1
Asset turnover	577	1.1098	0.7724	0.0151	7.6986
Cash flow					
Operating cash flow -margin	577	0.0825	0.4230	-5.8809	3.7813
GR mismatch					
Dummy	577	0.3136	0.4643	0	1
Industry disturbance					
Dummy	577	0.3275	0.4697	0	1
Indebtedness					
Leverage	577	0.2188	0.2033	0	1.2122
Gearing	577	0.4774	2.0923	-13.3151	15
Investment behavior					
Capex-margin	577	0.0761	0.1540	0	1
Liquidity					
Cash/Total assets	577	0.1435	0.1503	0	0.7978
Current ratio	577	1.7138	1.3523	0	20
Macro					
GDP-dummy	577	0.8977	0.3032	0	1

Table 7 provides descriptive statistics for target sample's 125 observations in prediction section. Descriptive statistics include mean, standard deviation, minimum and maximum values for all variables in the target sample's prediction section.

Table 7 Descriptive Statistics Prediction Section's Targets

Descriptive Statistics Prediction Section's Targets					
Variables	*Obs*	*Mean*	*St.dev*	*Min*	*Max*
Size					
Market capitalization (MEUR)	125	2.776,9	6,243.1	17.936	42,000.0
Enterprise value (MEUR)	125	4,720.4	10,900.0	48.425	62,600.0
Total assets (MEUR)	125	4,453.9	10,300.0	14.200	65,900.0
Net sales (MEUR)	125	2,360.8	5,565.4	0.017	45,100.0
Valuation					
P/E	125	16.2568	48.4638	-150	180.7619
P/B	125	3.5075	4.4392	0	31.6440
P/S	125	4.4091	15.3288	0.0672	100
EV/EBITDA	125	14.7790	18.8892	-10.1904	52.2344
Inefficient management					
1-year sales growth	125	0.2580	1.2385	-0.7492	13.0335
ROE	125	0.0636	0.5905	-5	3.9016
EBITDA-margin	125	0.1198	0.6724	-5	0.6672
Profit-margin	125	0.0034	0.2662	-1	1
Asset turnover	125	0.9096	0.5954	0	3.9428
Cash flow					
Operating cash flow -margin	125	0.0848	1.1747	-1	0.5380
GR mismatch					
Dummy	125	0.2240	0.4185	0	1
Industry disturbance					
Dummy	125	0.3280	0.4713	0	1
Indebtedness					
Leverage	125	0.2437	0.2053	0	1.1113

Gearing	125	0.2804	1.9812	-4.5	5.3070
Investment behavior					
Capex-margin	125	0.0688	0.1297	0	1
Liquidity					
Cash/Total assets	125	0.1485	0.1419	0	0.8209
Current ratio	125	1.7156	1.8524	0.1225	16.1111
Macro					
GDP-dummy	125	1	0	1	1

4.2.2 Non-Targets

The data for non-target sample is retrieved from DataStream database under criteria stated in the Chapter 4.2. Predefined constituent company lists per country were used when retrieving the data as the constituent company lists exclude all the companies which are targets of an acquisition in given years. The screen yielded 16 774 observations in Finland, Sweden, Norway, Denmark, Germany and France from 01.01.2001 to 31.12.2018. The non-target sample is further divided into two sections. All the 13 2018 observations from the period of 01.01.2001 to 31.12.2014 are classified as estimation sample, whereas all the 3 556 observations from 01.01.2015 to 31.12.2018 are classified as prediction sample. All 16 774 observations, i.e. firms in the non-target sample represents 96% of the whole data set, i.e. estimation and prediction sample combined.

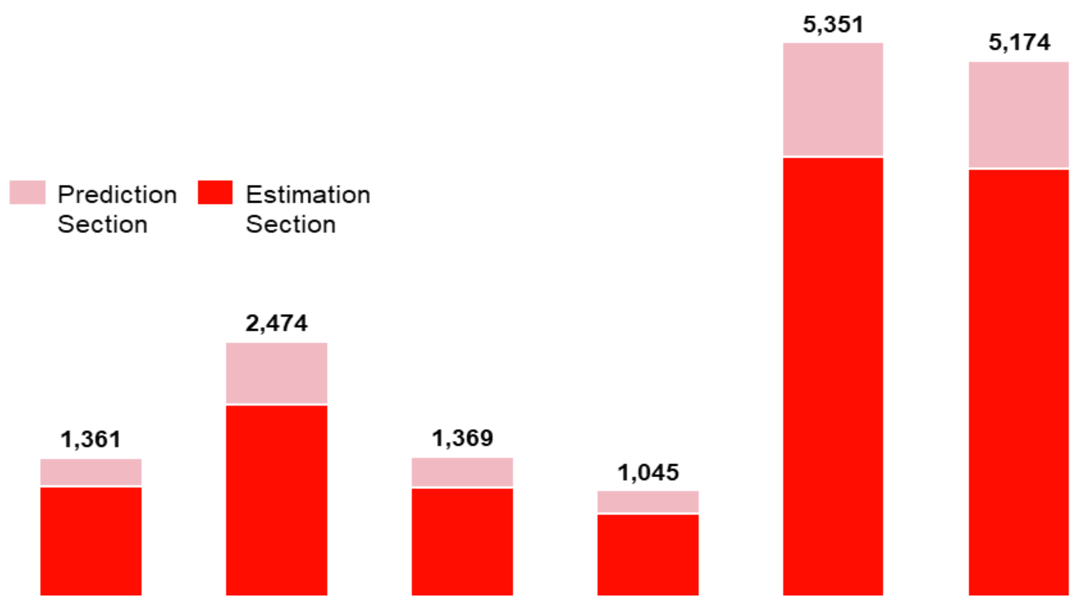

Figure 4 Non-Target Sample by country

As seen from the Figure 4, Germany and France represent the vast majority of observations in both estimation and prediction sections, whereas the number of observations in Denmark, Finland and Norway is relatively low in both sections. Moreover, it can be seen from the Figure 5 that the number of observations per year is relatively stable. The burst of the dot-com bubble, the financial crisis and the European debt crisis are all relevant factors affecting the observation volume, i.e. volume of listed companies in Germany, France and the Nordics. Nevertheless, reliable analysis explaining the variations of observation volume within different years is outside of this study.

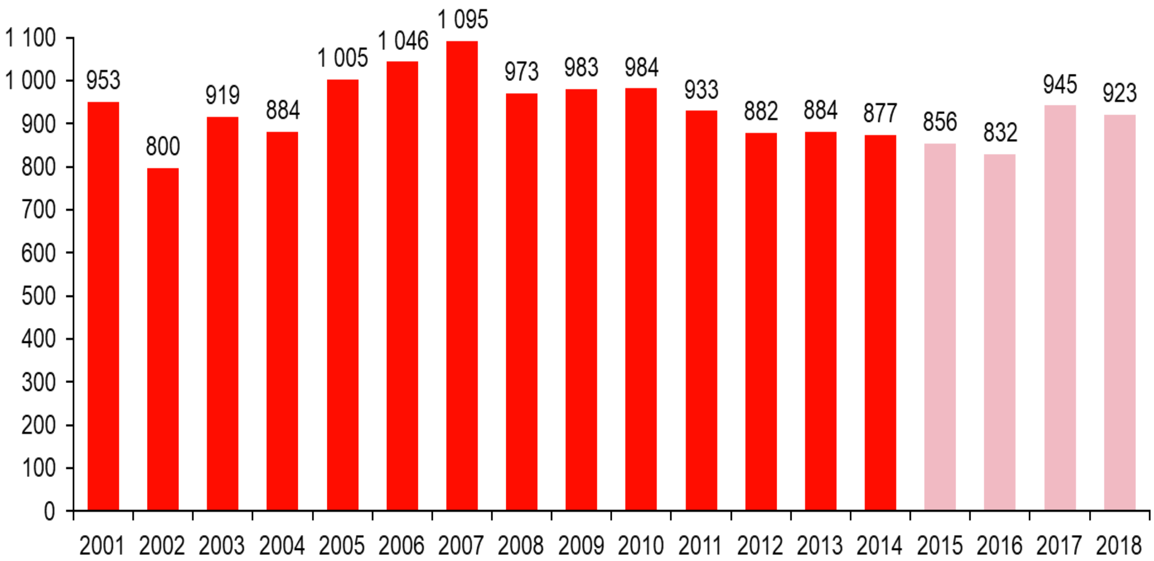

Figure 5 Non-Target Sample by years

Table 7 provides descriptive statistics for non-target sample's 13 218 observations in estimation section. Descriptive statistics include mean, standard deviation, minimum and maximum values for all variables in the non-target sample's estimation section.

Table 8 Descriptive Statistics Estimation Section's Non-Targets

Descriptive Statistics Estimation Section's Non-Targets					
Variables	*Obs*	*Mean*	*St.dev*	*Min*	*Max*
Size					
Market capitalization (MEUR)	13218	2,494.3	10,400.0	10.007	196,000.0
Enterprise value (MEUR)	13218	3,296.6	14,000.0	10.003	261,000.0
Total assets (MEUR)	13218	4,290.3	21,000.0	2.088	476,000.0
Net sales (MEUR)	13218	3,361.9	14,100.0	0.790	279,000.0
Valuation					
P/E	13218	16.6058	40.5106	-149.6366	398.6846
P/B	13218	2.4171	2.5807	0.0293	49.2311

P/S	13218	1.2616	2.2273	0.0080	57.9917
EV/EBITDA	13218	7.4252	18.4240	-100	100
Inefficient management					
1-year sales growth	13218	0.2556	1.6711	-0.8	45
ROE	13218	0.0376	0.3715	-4.9271	9.0258
EBITDA-margin	13218	0.1091	0.1737	-1.7273	5
Profit-margin	13218	0.0212	0.1436	-0.9965	0.9787
Asset turnover	13218	1.1841	0.6510	0.0095	8.1917
Cash flow					
Operating cash flow -margin	13218	0.0665	0.1663	-4.1271	3.5911
GR mismatch					
Dummy	13218	0.2349	0.4240	0	1
Industry disturbance					
Dummy	13218	0.2140	0.4101	0	1
Indebtedness					
Leverage	13218	0.2082	0.1647	0	2.0346
Gearing	13218	0.5501	1.1305	-11.0957	14.9158
Investment behavior					
Capex-margin	13218	0.0538	0.0898	0	0.9815
Liquidity					
Cash/Total assets	13218	0.0767	0.1013	0	1.0479
Current ratio	13218	1.8903	1.4840	0	19.5131
Macro					
GDP-dummy	13218	0.8454	0.3615	0	1

Table 8 provides descriptive statistics for non-target sample's 3 556 observations in prediction section. Descriptive statistics include mean, standard deviation, minimum and maximum values for all variables in the non-target sample's prediction section.

Table 9 Descriptive Statistics Prediction Section's Non-Targets

Descriptive Statistics Prediction Section's Non-Targets					
Variables	*Obs*	*Mean*	*St.dev*	*Min*	*Max*
Size					
Market capitalization (MEUR)	3556	4,058.7	13,600.0	10.063	169,000.0
Enterprise value (MEUR)	3556	5,130.5	18,300.0	10.047	259,000.0
Total assets (MEUR)	3556	5,979.5	26,900.0	3.548	538,000.0
Net sales (MEUR)	3556	4,260.9	15,800.0	0.743	283,000.0
Valuation					
P/E	3556	19.8197	37.3861	-150	391.6296
P/B	3556	2.8990	2.9622	0	44.6475
P/S	3556	1.6964	2.7593	0.0063	48.2064
EV/EBITDA	3556	10.0588	19.5345	-100	100
Inefficient management					
1-year sales growth	3556	0.0929	0.8850	-0.8	40
ROE	3556	0.0641	0.3161	-4.3776	3.8991
EBITDA-margin	3556	0.1183	0.1725	-1.9736	1.3518
Profit-margin	3556	0.0279	0.1541	-1	0.9401
Asset turnover	3556	1.0648	0.6036	0.0130	7.6140
Cash flow					
Operating cash flow -margin	3556	0.0773	0.1678	-2.0273	1.3362
GR mismatch					
Dummy	3556	0.2334	0.4230	0	1
Industry disturbance					

Dummy	3556	0.1757	0.3806	0	1
Indebtedness					
Leverage	3556	0.2117	0.1601	0	1.1879
Gearing	3556	0.3796	0.9517	-15	13.5290
Investment behavior					
Capex-margin	3556	0.0514	0.0864	0	0.9330
Liquidity					
Cash/Total assets	3556	0.1215	0.1203	0	0.9737
Current ratio	3556	1.8548	1.4061	0	18.9313
Macro					
GDP-dummy	3556	1	0	1	1

4.3 Methodology

This thesis ultimate objective is to introduce a highly reliable regression model with strong predictive power. Thus, the whole methodological process is divided into different steps and every step is conducted with precise accuracy. Firstly, estimation section's targets and non-targets are compared with each other in order to find significant differences. Then, to enhance the reliability of the model, correlation analysis and VIF-test, i.e. variance inflation factor tests, are employed. Thirdly, to estimate the acquisition likelihood based on the selected variables, logistic regression is used. Fourthly, based on regression model's results, i.e. takeover probabilities, classification among targets and non-targets is conducted within prediction section by determining the proper cut-off value.

4.3.1 Variable validation

T-tests are conducted for every variable of the ten hypotheses. Objective is to find statistically significant differences between estimation section's target sample (n=577) and non-target sample (n=13 218). Based on the results of t-tests, the most statistically significant variables are selected as variables to the logistic regression model, whereas the most insignificant variables are dropped.

The null hypothesis is assumed as H_0: $\bar{x}_1 - \bar{x}_2 = 0$ and the alternative hypothesis is assumed as H_1: $\bar{x}_1 - \bar{x}_2 \neq 0$. The statistical comparison of the means can be calculated with the following formula:

$$t = \frac{(\bar{x}1 - \bar{x}2) - (\bar{\mu}1 - \bar{\mu}2)o}{\sqrt{s\rho^2(\frac{1}{n_1} + \frac{1}{n_2})}}, \quad (1)$$

where

$$s\rho^2 = \frac{(n1-1)s1^2(n2-1)s2^2}{n_1-n_2-2}. \tag{2}$$

As the significant and insignificant variables are identified, multicollinearity of variables is analyzed by employing correlation matrix as well as conducting VIF-tests. Estimation section's target sample and non-target sample are combined at this point when reliability of variables is under scrutiny. Variables which contain strong correlation, i.e. a correlation higher than an absolute value of 0.8, are excluded. Moreover, variables which have value higher than ten in VIF-tests are excluded as well due to multicollinearity.

4.3.2 Statistical model

To test the hypotheses, the dependent variable called ''Targetdummy''is regressed on the independent variables based on the hypotheses. Targetdummy gets value one if a firm belongs to target sample and value zero if a firm belongs to non-target sample. The objective is to specify the exact functional relationship between the firm characteristics and acquisition likelihood in a given period.

Logistic regression model is selected due to its applicable use within takeover prediction as the range of probability values is limited from zero to one, whereas linear logistics regression model might produce values less than zero and higher than one. Therefore, logistic regression is seen as more appropriate model for takeover prediction. Equation of logistic regression model determined by Palepu (1986, 15) is as follows:

$$\mathrm{p}(\mathrm{i},\mathrm{t}) = \frac{1}{1+e^{-\beta x(i,t)}}, \tag{3}$$

where $p(i,t)$ the probability that firm i is acquired in period t, $x(i, t)$ vector of independent firm- and industry variables and β vector of parameters to be estimated.

Alternatively, the equation can be expressed linearly. Below is an example of linear equation where ‘’Targetdummy’’, i.e. the dependent variable, is regressed on the Model V’s independent variables.

$$Targetdummy = \beta_0 + \beta_1 Ln(Market\ capitalization)_i + \beta_2 Ln(Total\ assets)_i + \beta_3 P/E_i + \beta_4 P/B_i + \beta_5 P/S_i + \beta_6 EV/EBITDA_i + \beta_7 ROE_i + \beta_8 EBITDAmargin_i + \beta_9 Asset\ turnover_i + \beta_{10} GR\ dummy_i + \beta_{11} Industry\ disturbance\ dummy_i + \varepsilon_i. \quad (4)$$

In order to further enhance the accuracy and reliability of the prediction model, conditional logistic regression model is employed. Conditional logistic regression differs from simple logistic regression in that the data are grouped and the probability is relative to each group, i.e. conditional likelihood is employed. Conditional logistic regression model enables comparison of more relevant observations with each other as firms in the target sample are matched with firms in the non-target sample by the year of the observation and by an industry, i.e. SIC code. Therefore, acquisition targets operating in technology industry in 2018, for instance, are not compared with non-target firms operating in metal industry in 2001, but with non-target technology firms in 2018. Such a matching is assumed to enhance the prediction power of the model as macroeconomic environment varies across the years and different factors explain M&A activity among different industries, e.g. Tsagkanos et al. (2006) found conditional logistic regression models to have superior prediction power compared to simple logistic regression models. Targets are not matched against non-targets as 1:1, but as 1:n. Thus, one target firm can be matched with several non-target firms within a matched group. In other words, if one target firm and three non-target firm were operating in 2010 in transportation sector, the one target firm’s variables are compared with the three non-target firms’ variables. Furthermore, there is no need to rearrange the data with conditional logistic regression, the data is arranged as panel data for both statistical methods, simple logistic and conditional logistic regressions.

In order to find the significance of matching targets and non-targets by years and industries, normal logistic regression, i.e. unconditional logistic regression, models are run as well. Altogether eight regression models will be constructed and run. Four of them are simple logistic regression models and four of them are conditional logistic regression models. All models are calculated with STATA statistical program.

4.3.3 Prediction accuracy

Regression models, which are developed based on estimation section's data, are run within prediction section's data as an out of sample test. All observations in the prediction section are classified as predicted targets and predicted non-targets based on the logistic regression model's estimated probabilities. Classification among predicted targets and predicted non-targets is conducted with predefined cut-off probability. According to Palepu (1986, 11-14) the cut-off probability, which minimize the overall sample error rare, is derived from estimation section's probability distributions for target sample and non-target sample. The cut-off value is the value where these two probability density functions intersect. In practice, the optimal cut-off value is derived based on three steps. First, logistic regression models are run within the estimation section data to get takeover probabilities for all firms. Second, probability density functions for targets and non-targets are modelled based on firms' takeover probabilities. Third, these two probability density functions are graphically plotted, and the optimal cut-off value is where these to probability density functions intersect. If the estimated probability for a firm is higher than the cut-off value, the firm is classified as predicted target and vice versa. Then, all prediction section's predicted targets are compared with prediction section's actual targets and all prediction section's predicted non-targets are compared with prediction section's actual non-targets in order to test the model's prediction accuracy.

5 EMPIRICAL RESULTS

The overall methodological process is divided into three separate sub-processes in order to derive reliable empirical results. First, statistical significance and reliability of variables is tested with t-tests and VIF-tests. All unreliable and insignificant variables are dropped in this respect. Secondly, conditional logistic regression model is employed in order to construct prediction model for publicly listed companies. Thirdly, prediction accuracy is tested by defining cut-off value.

5.1 Validation of variables

T-tests are run in order to find statistically significant differences in the means of targets and non-targets, i.e. differences in estimation section's target and non-target samples. In this respect, no matching by year of the observation or the SIC code is done. Most of the variables, i.e. 18 variables out of 21 variables, show statistically significant results. Several hypotheses are confirmed, and some hypotheses are rejected due to inconsistent results in the t-tests. All results in the t-tests are provided in the Table 10.

All four variables show larger means for non-targets than targets in the t-tests. Variables total assets and net sales have p-values of 0.0082 and 0.0052, respectively. Thus, both variables are highly statistically significant. Market capitalization variable is statistically significant as well as the p-value is 0.0336. Enterprise value is the only size variable, which is not statistically reliable as its p-value is at 0.4937. Hence, it can be stated that target companies are smaller by size and the size hypothesis can be fully confirmed.

All four valuation multiples, i.e. P/E, P/B, P/S and EV/EBITDA, contain significant differences in the means of targets and non-targets. Without exception, averages within target sample are bigger than averages within non-target sample. In addition, every valuation variable is significant at 1% p-value. With these consistent results, valuation hypothesis is confirmed.

Variables linked to inefficient management show inconsistent results. 1-year sales growth, ROE and EBITDA and Profit margins indicate higher efficiency within target sample, whereas Asset turnover indicate an opposite relationship. Asset turnover is the only variable of the all five variables being significant at 1% p-value, whereas ROE and EBITDA-margin are significant at 5% p-value and 1-year sales growth and Profit-margin are both insignificant. Due to mixed results, efficient management hypothesis cannot be fully confirmed.

According to t-test results, targets do have higher cash flows than non-targets. Operating cash flow margin for targets is 8.25%, whereas it is for non-targets 6.66%. The variable is significant at 5% p-value, p-value being 0.0211. Therefore, cash flow hypothesis is confirmed. Growth-resource mismatch hypothesis is confirmed as well. The higher the dummy variable, the higher the mismatch and the higher the mismatch, the higher the probability to be taken over. The dummy variable is distinctly higher for targets than non-targets, and the variable is highly significant at 1% p-value, p-value being 0.0000.

Variables representing indebtedness level show contrary results in the t-tests. On one hand, leverage ratio is higher for targets than non-targets, and on the other hand, gearing-ratio is higher for non-targets than targets. Gearing ratio has larger difference in the means than leverage ratio but has slightly statistically weaker p-value. Both variables are statistically significant at 10 % p-value. Thus, it cannot be confirmed that target companies operate at higher indebtedness levels than non-target companies and indebtedness hypothesis is rejected.

T-tests for two variables indicating liquidity show opposite results with each other. Cash to total assets -ratio is distinctly higher for targets than non-targets, whereas current ratio is higher for non-targets. Both variables, cash-to total assets ratio and current ratio are significant at 1% p-value, p-values being 0.0000 and 0.0025, respectively. Thus, cash to total asset variable is statistically more reliable and the difference in the means is relatively much larger than within current ratio. Nevertheless, due to mixed results, liquidity hypothesis cannot be fully confirmed.

According to t-test results, target companies invest more in capital expenditures than non-target companies, capex-margin means being 7.62% and 5.38%, respectively. P-value for capex-margin is 0.0000, which is highly significant result. Therefore, investment behavior hypothesis is confirmed. Industry disturbance hypothesis is confirmed as well. The dummy variable, which indicate positive correlation with previous transactions within an industry and takeover likelihood, is clearly higher for target companies than non-target companies. The dummy variable's p-value is 0.0000, i.e. the variable is statistically highly significant. Moreover, macroeconomic condition hypothesis is confirmed. The GDP-dummy variable is clearly higher for target companies than non-target companies, as the means are 0.898 and 0.845 respectively. P-value of 0.0003 indicate high statistical significance of the variable.

In order to further enhance the model's reliability correlation matrix is constructed and VIF-tests are run. Correlation matrix show interdependencies among many variables at significance level of 5 %. However, generally only weak correlations are found among variables. As the variables can be classified into different sub-groups according to their linked hypotheses, size variables -group is the only group where strong interdependencies are found within variables. Enterprise value, in particular, correlates strongly with other size variables as the correlation is higher than 0.8 with every variable. Moreover, variables net sales and total asset have positive correlation of 0.8916 with each other. In addition to size variables, profit margin is found to correlate semi-strongly, i.e. 0.4918-0.6886 correlations at 0.0000 p-value, with ROE, EBITDA-margin and operating cash flow -margin. Moreover, indebtedness variables, i.e. leverage and gearing ratios do have semi-strong positive relationship with each other, correlation being 0.6732 at 0.0000 p-value. Correlation matrix is provided in Table 11.

None of the variables has VIF-value above 10, which would indicate severe multicollinearity. Enterprise value variable has the highest variance inflation factor of 9.65, whereas the overall average VIF-value is 2.57. In other words, multicollinearity among variables cannot be seen as an issue.

To ensure statistical reliability of the model variables that are statistically insignificant, have high correlation with other variables and contain high variance inflation factor are excluded. Therefore, the following variables are dropped; enterprise value, total assets, profit-margin, 1-year sales growth and gearing ratio. Hence, logistic regressions are constructed with the remaining 17 variables.

Table 10 T-tests results

Parameters that are significant at 1%, 5% or 10% level are marked with ***, ** and *.

	T-tests				
	Targets	*Non-targets*	*Diff*	*t-value*	*p-value*
Size					
Market capitalization	1694333	2494323	799991	1.8302**	0.0336
Enterprise value	3286986	3296601	9614	0.0158	0.4937
Total assets	2185619	4290288	2104669	2.3997***	0.0082
Net sales	1870166	3361989	1491824	2.5223***	0.0058
Valuation					
P/E	24.7	16.6	-8.1	-4.55***	0.0000
P/B	3.4	2.4	-1	-8.4288***	0.0000
P/S	2.4	1.3	-1.1	-9.7920***	0.0000
EV/EBITDA	13.4	7.4	-6	-7.5758***	0.0000
Inefficient management					
1-year sales growth	26.12	25.56	-0.0056	-0.0789	0.4685
ROE	0.0716	0.0377	0.3161	-2.1256**	0.0168
EBITDA-margin	0.1091	0.0925	0.1666	2.0010**	0.0227
Profit-margin	0.0272	0.0212	-0.006	-0.9583	0.1690
Asset turnover	1.1098	1.1841	0.0743	2.6610***	0.0039
Cash flow					

Operating cash flow -margin	0.0825	0.0666	-0.0159	-2.0321**	0.0211
GR mismatch					
Dummy	0.3137	0.2350	-0.0787	-4.3467***	0.0000
Indebtedness					
Leverage	0.2188	0.2083	-0.0105	-1.4892*	0.0682
Gearing	0.4774	0.5501	0.0727	1.4404*	0.0749
Liquidity					
Cash to Total assets	0.1435	0.0767	-0.0668	-15.1276***	0.0000
Current ratio	1.7138	1.8904	0.1765	2.8070***	0.0025
Investment behavior					
Capex-margin	0.0762	0.0538	-0.0224	-5.6259***	0.0000
Industry disturbance					
Dummy	0.3276	0.2140	-0.1135	-6.4664***	0.0000
Macro					
GDP-dummy	0.8977	0.8454	-0.0523	-3.4236***	0.0003

Table 11 Correlation matrix

Correlation is significant at 10% level within parameters when it is marked with *.

Correlation matrix 1/4

	Market Cap	*EV*	*Net Sales*	*Total assets*	*P/E*
Market Cap	1.00				
EV	0.91*	1.00			
Net Sales	0.75*	0.82*	1.00		
Total Assets	0.75*	0.85*	0.89*	1.00	
P/E	0.01	0.01	-0.01	-0.01	1.00
P/B	0.05	0.02*	-0.04*	-0.04*	0.1*
P/S	0.03	0.01	-0.05*	-0.03*	0.08*
EV/EBITDA	0.03	0.03*	-0.01	0.00	0.18*
Sales growth	-0.01	-0.01	-0.02*	-0.01	-0.01
ROE	0.07*	0.06*	0.04*	0.03*	0.11*
Profit-mar.	0.09*	0.07*	0.03*	0.03*	0.15*
EBITDA-mar.	0.09*	0.09*	0.03*	0.05*	0.11*
Asset turnover	-0.11*	-0.12*	-0.06*	-0.12*	-0.02*
Opera. mar.	0.09*	0.08*	0.04*	0.05*	0.09*
Gearing	0.01	0.08*	0.09*	0.11*	-0.04*
Leverage	0.01	0.07*	0.06*	0.07*	-0.04*
Current ratio	-0.08*	-0.09*	-0.10*	-0.09*	0.04*
Cash-Totalas.	-0.02*	-0.03*	-0.02*	-0.03*	0.01
Capex-margin	0.03*	0.04*	0.01	-0.04*	0.02*
ID-Dummy	-0.01	-0.01	-0.01	-0.01	0.00
GR-dummy	-0.01*	-0.03*	-0.03	-0.03	0.01
GDP-dummy	0.02*	0.02*	0.00	0.00	0.03*

Correlation matrix 2/4

	P/B	*P/S*	*EV/EBITDA*	*Sales Growth*	*ROE*
P/B	1.00				
P/S	0.39*	1.00			
EV/EBITDA	0.09*	0.03*	1.00		
Sales Growth	0.06*	0.11*	0.01	1.00	
ROE	0.02*	0.02*	0.12*	0.00	1.00
Profit-mar.	0.04*	-0.01	0.19*	-0.04*	0.6*
EBITDA-mar.	0.03*	-0.02*	0.15*	-0.01	0.39*

Asset turnover	0.11*	-0.27*	-0.02	-0.04*	0.06*
Opera. mar.	-0.01	-0.04	0.12*	-0.02*	0.25*
Gearing	0.02*	-0.13*	0.01	0.00	-0.19*
Leverage	-0.12*	-0.17*	0.03*	0.00	-0.11*
Current ratio	0.04*	0.32*	0.00	0.03*	0.07*
Cash-Totalas.	0.13*	0.16*	-0.03*	0.01	0.04*
Capex-margin	-0.03*	0.14*	-0.01	0.04*	-0.02*
ID-Dummy	0.02*	0.02*	0.01	0.02*	-0.02*
GR-dummy	0.02*	0.01	0.00	0.02*	0.02*
GDP-dummy	0.06*	0.04*	0.02*	0.00	0.01

Correlation matrix 3/4

	Profit-mar.	*EBITDA-mar.*	*Asset turnover*	*Opera. mar.*	*Gearing*
Profit-mar.	1.00				
EBITDA-mar.	0.69*	1.00			
Asset turnover	0.02*	-0.16*	1.00		
Opera. mar.	0.49*	0.51*	-0.09*	1.00	
Gearing	-0.08*	0.02*	-0.08*	-0.01	1.00
Leverage	-0.07*	0.08*	-0.17*	0.03*	0.67*
Current ratio	0.09*	0.04*	-0.11*	-0.03*	-0.24*
Cash-Totalas.	0.02*	-0.01	-0.06*	0.02	-0.31*
Capex-margin	-0.01	0.14*	-0.31*	0.08*	0.10*
ID-Dummy	-0.02*	-0.02*	-0.02	-0.01	0.00
GR-dummy	0.03*	0.01	0.01	0.00	-0.15*
GDP-dummy	0.02	0.02*	-0.03*	0.01	-0.02

Correlation matrix 4/4

	Lever-age	*Current ratio*	*Cash-Total ass.*	*Capex-margin*	*ID-Dummy*	*GR-Dummy*	*GDP-dummy*
Leverage	1.00						
Current ratio	-0.32*	1.00					
Cash-Totalas.	-0.25*	0.27*	1.00				
Capex-margin	0.22*	0.02*	-0.02*	1.00			
ID-Dummy	-0.02*	0.02*	0.02*	-0.01	1.00		
GR-dummy	-0.18*	0.11*	0.37*	-0.03	0.02	1.00	
GDP-dummy	-0.02*	0.00	0.03*	-0.01	-0.02*	-0.02*	1.00

5.2 Statistical model

All together eight regression models are constructed and run. In order to detect the effect of matching observations/deals with year and SIC-code, both conditional logistic regression models and simple logistic regression models are constructed and run concurrently. In other words, the first three models are identical to their equivalent models, only difference being the employment of matching.

The first model is fully based on Palepu's (1986) hypotheses and it is constructed accordingly. The objective is to observe if Palepu's findings still holds in 2000 century.

The second model incorporates all the variables used in the first model but as well all the remaining variables linked to cash flow hypothesis, indebtedness hypothesis, liquidity hypothesis and investment behavior hypothesis. Thus, the second model incorporates all the variables, except GDP-dummy variable, which were chosen in the Chapter 5.1. All the chosen variables are firm specific, only exception being industry disturbance dummy. Therefore, the third model is identical to the second one, but industry disturbance dummy is excluded as its significance is wanted to be examined.

The fourth model is identical to the third model, only exception being more accurate matching. Within the models I, II and III the matching is conducted by the year of the deal/observation and the 3-digit SIC-code, whereas the model IV's matching is conducted by the year of the deal/observation and 4-digit SIC-code, which is more accurate industry classification than 3-digit SIC-code. The first three models are matched only with 3-digit SIC-code, because with 4-digit SIC-code no within group variance was found with industry disturbance dummy. Thus, the variable was omitted in every conditional logistic regression with 4-digit SIC-code matching. Therefore, in order to incorporate the industry disturbance dummy variable as well to regression model, slightly less accurate matching is justified.

Based on the models' results, it can be stated that employment of matching increases the explanatory power of models. Firstly, as seen in the Table 11 and Table 12, the pseudo R^2 of Model I, Model II and Model III is without exception higher than in their equivalent models of Model V, Model VII and Model VI, respectively. Secondly, the pseudo R^2 for the Model IV is significantly higher than in Model III. The difference in the pseudo R^2 can be stated significant as the two models are identical with each other the only difference being slightly more accurate matching by the four digit SIC-code instead of three digit SIC-code matching in the Model IV. Nevertheless, conditional logistic regressions do not perform better when it comes to the Likelihood Ratio, (LR). In fact, all simple logistic regression models perform better than their equivalent conditional regression models in terms of Likelihood Ratio. The number of observations varies across models. First three models have 5015 observations, the fourth model has 3062 observations and the last four models have 13975 observations.

Statistical significance of variables varies substantially across different models. ROE is the only variable which show no significance in any model and in every model there are at least three variables which are not statistically significant. Nevertheless, a vast majority of variables are significant at least at p>0.1 level. Tables 10 and 11 provide all coefficient of variables and their respective t-values.

Table 12 Regression models I-IV

Parameter estimates with t-values in parentheses are given for four models. Sample size is 5015 observations in first three models and 3062 in the fourth model. Parameters that are significant at 1%, 5% or 10% level are marked with ***, ** and *.

	Model I	Model II	Model III	Model IV
Size				
(LN) Market cap	**0.243*****	**0.342*****	**0.336*****	**0.376*****
	(2.95)	(3.41)	(3.35)	(3.18)
(LN) Total assets	**-0.083**	**-0.198****	**-0.194***	**-0.195***
	(-1.03)	(-2.00)	(-1.95)	(-1.68)
Valuation				
P/E	**0.001**	**0.001**	**0.001**	**0.001**
	(1.48)	(1.13)	(1.15)	(0.51)
P/B	**0.036****	**-0.002**	**-0.000**	**0.006**
	(2.18)	(-0.11)	(-0.01)	(0.27)
P/S	**0.042****	**0.056****	**0.056****	**0.069**
	(2.07)	(2.27)	(2.25)	(2.47)
EV/EBITDA	**0.013*****	**0.015*****	**0.015*****	**0.013*****
	(4.98)	(5.47)	(5.47)	(4.3)
Inefficient management				
ROE	**0.146**	**0.176**	**0.160**	**0.209**
	(0.98)	(1.25)	(1.17)	(1.15)
EBITDA-margin	**-0.969*****	**-1.166*****	**-1.136*****	**-0.882****
	(-3.72)	(-3.63)	(-3.57)	(-2.55)
Asset turnover	**-0.185****	**-0.050**	**-0.057**	**-0.061**
	(-2.04)	(-0.51)	(-0.58)	(-0.55)
GR mismatch				
Dummy	**0.518*****	**0.117**	**0.124**	**0.196**
	(4.69)	(0.94)	(0.99)	(1.35)
Industry disturbance				
Dummy	**0.428****	**0.469****		
	(2.35)	(2.48)		
Cash Flows				
Operating cash flow		**0.468***	**0.466***	**0.383**
		(1.68)	(1.68)	(1.25)
Indebtedness				
Leverage		**1.070*****	**1.054*****	**0.702**
		(2.64)	(2.6)	(1.51)
Liquidity				
Cash to total assets		**6.377*****	**6.370*****	**6.750*****
		(12.99)	(13.01)	(11.40)
Current ratio		**-0.350*****	**-0.348*****	**-0.418******
		(-5.75)	(-5.69)	(-5.76)
Investment behavior				
Capex-margin		**1.560*****	**1.508*****	**1.412****
		(3.05)	(2.97)	(2.54)
Number of obs	5015	5015	5015	3062
LR chi^2 (11-18)	168.83	376.91	370.63	325.83
Prob > chi^2	0.00000	0.0000	0.0000	0.0000

Pseudo R^2	0.0736	0.1642	0.1615	0.2074

Table 13 Regression models V-VIII

Parameter estimates with t-values in parentheses are given for three models. Sample size is 13 795 observations in all models. Parameters that are significant at 1%, 5% or 10% level are marked with ***, ** and *.

	Model V	Model VI	Model VII	Model VIII
Size				
(LN) Market cap	**0.150****	**0.270*****	**0.276*****	**0.259*****
	(2.34)	(3.59)	(3.68)	(3.42)
(LN) Total assets	**0.028**	**-0.109**	**-0.112**	**-0.095**
	(0.45)	(-1.45)	(-1.49)	(-1.26)
Valuation				
P/E	**0.002****	**0.002****	**0.002****	**0.002****
	(2.06)	(2.22)	(2.18)	(2.14)
P/B	**0.0412*****	**-0.006**	**-0.009**	**-0.008**
	(3.12)	(-0.36)	(-0.58)	(-0.51)
P/S	**0.039*****	**0.058*****	**0.059*****	**0.059*****
	(3.00)	(3.76)	(3.86)	(3.97)
EV/EBITDA	**0.013*****	**0.015*****	**0.015*****	**0.015*****
	(6.24)	(6.91)	(6.77)	(6.79)
Inefficient management				
ROE	**0.173**	**0.180**	**0.200**	**0.201**
	(1.32)	(1.36)	(1.50)	(1.51)
EBITDA-margin	**-0.796*****	**-0.893*****	**-0.861*****	**-0.885*****
	(-4.08)	(-3.78)	(-3.59)	(-3.68)
Asset turnover	**-0.051**	**0.123**	**0.136***	**0.141***
	(-0.67)	(1.57)	(1.73)	(1.8)
GR mismatch				
Dummy	**0.408*****	**0.149**	**0.141**	**0.151**
	(4.33)	(1.45)	(1.37)	(1.46)
Industry disturbance				
Dummy	**0.576*****		**0.589*****	**0.593*****
	(6.21)		(6.22)	(6.26)
Cash Flows				
Operating cash flow		**0.238**	**0.205**	**0.220**
		(1.15)	(0.98)	(1.06)
Indebtedness				
Leverage		**1.217*****	**1.240*****	**1.219*****
		(3.83)	(3.91)	(3.84)
Liquidity				
Cash to total assets		**4.997*****	**5.001*****	**4.967*****
		(13.97)	(13.89)	(13.79)
Current ratio		**-0.310*****	**-0.313*****	**-0.31******
		(-6.32)	(-6.38)	(-6.33)
Investment behavior				
Capex-margin		**1.436*****	**1.479*****	**1.510****
		(3.86)	(3.95)	(4.04)
Macro				
GDP-dummy				**0.379*****
				(2.62)
Number of obs	13 795	13 795	13 795	13 795
LR chi^2 (11-18)	248.34	431.85	468.11	475.56

Prob > chi^2	0.00000	0.0000	0.0000	0.0000
Pseudo R^2	0.0518	0.0901	0.0977	0.0992

5.3 Prediction accuracy

In order to classify targets and non-targets specific cut-off values are determined for every model. A cut-off value, which minimize the overall sample error rate, equals the value where estimation section's probability density functions for targets and non-targets intersect (Palepu, 1986 11-14). In practice the optimal cut-off value is derived based on the following three steps. First, logistic regression models are run within the estimation section data to get takeover probabilities for all firms. Second, probability density functions for targets and non-targets are modelled based on firms' takeover probabilities. Third, these two probability density functions are graphically plotted, and the optimal cut-off value is where these to probability density functions intersect. As every model yields different takeover probabilities, every eight model has different cut-off values.[2] Cut-off values range from 0.04 to 0.145 within models and the results show clearly that the cut-off values are higher in conditional logistic regressions than in simple logistic regressions.

After the regression models and cut-off values are determined based on estimation section's data, the eight regression models with exactly same model compositions are run again within prediction section's data as an out of sample test. Classification among targets and non-targets is conducted based on predefined cut-off values for every model and yielded takeover probabilities by re-running regression models within prediction section's data.

Every single simple logistic regression model outperforms their equivalent conditional logistic regression models in terms of prediction accuracy. The best performing conditional logistic regression model, Model II, predicts 48% of the targets and 49.76% of the non-targets correctly, totaling prediction accuracy of 49.72%. In other words, a toss of a coin has better prediction capability than the best performing conditional logistic regression model. However, the best performing simple logistic regression model, Model VII, predicts correctly 63.20% of targets and 59.90% of non-targets, totaling prediction accuracy of 60.01%. These results are in line with other corresponding studies such as

[2] Probability density functions for all models are provided in the Appendix 6.

Simkowitz & Monroe (1971). Still, it should be noted that the results contain a negative relationship between prediction accuracy and models' explanatory power measured by pseudo R2. In other words, the Model VII has the best capability to classify targets and non-targets correctly, but it is not the most reliable model among all the eight regression models. Prediction performance and cut-off values are provided in the TABLES 13 and 14 for all the eight models.

Albeit the Model VII has the highest prediction power its composition of variables is unlikely the best possible one among all eight models. This thesis believes that Model VIII has the best variable composition of all eight models, at least in longer time-periods. It is likely that Model VII outperforms Model VIII in prediction accuracy due to relatively short time-period of three years of the prediction section's data. Every six countries of prediction section enjoyed economic growth in terms of GDP in every year between 2015 to 2018. Therefore, GDP-dummy for every prediction sample's observation is denoted as 1. Thus, prediction power of Model VIII decreases due to lack of variance in GDP-dummy. This thesis finds four arguments backing GDP-dummy's incorporation into regression models. First, t-tests prove the variable to be statistically significant and clear difference is found between targets and non-targets with estimation section's data, including 14 years with different macroeconomic conditions. Second, Model VIII outperforms Model VII both in terms of pseudo R2 and Likelihood Ratio, the only difference of the two models is employment of the GDP-dummy. Third, albeit Model VIII's total prediction accuracy is lower than Model VII's, prediction accuracy of targets is significantly higher, 66.4% and 63.2%, respectively. Fourth, Model VIII succeeds better classify target companies than Model VII in in-sample tests with estimation section's data.

In-sample tests were run in order to detect potential differences in prediction accuracies. In-sample tests, i.e. logistic regressions run with estimation section's data, show dramatically higher results for every model. For instance, Model VII scores accuracy of 60.00% in out-of-sample test, whereas the same model scores prediction accuracy of 75.40% in in-sample test. This fundamental difference of 15.40% highlights the importance of out-of-sample tests' utilization.

Table 14 Prediction accuracy results of Models I-V

	Model I	Model II	Model III	Model IV
Cut-off value	0.09	0.085	0.0825	0.145
Predicted Targets	63	60	61	73
Actual Targets	125	125	125	125
Targets Correct (%)	50.40%	48.00%	48.80%	58.4%
Predicted Non-Targets	1668	1770	1750	1540
Actual Non-Targets	3556	3556	3556	3556
Non-Targets Correct (%)	46.91%	49.75%	49.21%	43.31%
Total Observations	3681	3681	3681	3681
Total Correct	1731	1830	1811	1613
Total Correct (%)	47.03%	49.71%	49.20%	43.82%

Table 15 Prediction accuracy of Models V-VIII

	Model V	Model VI	Model VII	Model VIII
Cut-off value	0.04	0.05	0.05	0.049
Predicted Targets	77	79	79	83
Actual Targets	125	125	125	125
Targets Correct (%)	61.60%	63.20%	63.20%	66.4%
Predicted Non-Targets	1761	2033	2130	2007
Actual Non-Targets	3556	3556	3556	3556
Non-Targets Correct (%)	49.52%	57.17%	59.79%	56.44%
Total Observations	3681	3681	3681	3681
Total Correct	1838	2112	2205	2090
Total Correct (%)	49.93%	57.38%	60.01%	56.78%

6 SUMMARY AND CONCLUSIONS

The objective of this thesis is to construct as accurate and as reliable takeover prediction model as possible. Such a model would be useful in many different ways and for many different stakeholders. An ability to generate abnormal returns in stock markets is perhaps the most obvious area of utilization of accurate takeover prediction models. Nevertheless, this thesis's primary motivation is to achieve a higher level of understanding of the ambiguous factors affecting takeover likelihood. Without such an understanding a comprehensive and workable model cannot be constructed. Thus, the focus of this thesis in on the variables and predictive power of takeover prediction models.

This thesis contributes to the existing academic literature of takeover prediction in four relevant ways. Firstly, geographical area of study is expanded to cover the Nordic countries alongside with Germany and France as the vast majority of studies have focused on takeovers in United States or United Kingdom. Secondly, exceptionally long and comprehensive data set is employed covering all the years from 2001 to 2018. This long-time frame incorporates many exceptional macroeconomic periods such as the dotcom bubble, the financial crisis, long recovery from the financial crisis in historically low interest rate environment as well as the European debt crisis. Thirdly, macroeconomic aspect of mergers and acquisitions is included in this thesis. The aspect is studied country by country basis in order to find how different macroeconomic conditions of countries affect acquisition likelihood in a firm level. Fourthly, the empirical approach of the study is extended to employ simple logistic regressions as well as conditional logistic regressions in order to examine the effects of conditional matching and to compare accuracy as well as reliability of two different models.

All the eight regression models used in this thesis are based on ten hypotheses of takeover likelihood. Hypotheses for size, valuation, inefficient management, growth-resource mismatch and industry disturbance are based on Palepu's (1986) mostly cited paper in the takeover prediction literature. Furthermore, hypotheses for cash flows, indebtedness, liquidity, investment behavior and macroeconomic condition are incorporated to this thesis in order to construct comprehensive takeover prediction model. The lastly named hypotheses are based on academic literature and author's own assumptions.

Seven of the ten hypotheses are fully confirmed, namely; size hypothesis, valuation hypothesis, growth-resource mismatch hypothesis, industry disturbance hypothesis, cash flow hypothesis, investment behavior hypothesis and macroeconomic condition hypothesis. Inefficient management hypothesis was not confirmed due to inconsistent results. Asset turnover variable is in line with the hypothesis, but EBITDA-margin and ROE indicate higher efficiency for targets. Indebtedness hypothesis can be neither confirmed as leverage variable and gearing variable show contrary results with each other. Moreover, liquidity hypothesis consists inconsistent results. Cash to total assets -variable is distinctly higher for targets than non-targets, whereas current ratio is higher for non-targets.

Albeit three hypotheses are rejected due to inconsistent results, the variables linked to these hypotheses are still found to enhance the predictive power and reliability of the employed regression models. For instance, the most predictive coefficients as well as the most reliable results in t-tests are found within cash to total assets variable. Altogether, 17 variables are included into regression models of the 22 introduced variables. Five variables were dropped from regression models due to insufficient t-test results, low VIF-values or strong correlations.

Four simple logistic regression models as well as four conditional logistic regression models were constructed. Three conditional logistic regression models were matched by 3-digit SIC code and the year of the observation, whereas the fourth conditional logistic regression model was matched by 4-digit SIC code and the year of the observation. This thesis finds conditional matching to enhance the models' statistical reliability as the conditional regression models have higher Pseudo R2 results than their respective simple regression models. Nevertheless, this thesis finds simple logistic regression models to outperform their respective conditional regression models in terms of prediction accuracy.

Prediction accuracy tests were conducted for all eight regression models. The tests were run with prediction section's data as an out-of-sample tests ensuring statistical reliability of the study. Every model yields specific takeover probabilities for all firms and these probabilities were compared to predefined cut-off values. None of the conditional logistic regression models reached prediction rate over 50 %. Therefore, utilization of these models as an investment strategy is unlikely profitable. Nonetheless, simple logistic regressions model achieved more accurate prediction results. Models VI, VII and VII all achieved over 50 % total accuracy. The best performing model, Model VII, correctly predicts 63.20 % of targets and 59.79 % of non-targets, totaling 60.01 % accuracy. This result is in line with previous findings of academic literature.

This thesis has three suggestions for further research. Firstly, the effect of macroeconomic environment should be studied in more depth and in more detail. This thesis employs only one dummy variable indicating macroeconomic condition of a given year. More variables explaining macroeconomic environment could be added. Interest rates, exchange rates, consumers' confidence and stock market's volatility are examples of areas in need of more research in takeover prediction literature. Secondly, existing literature has neglected analyzation of acquirers to a great extent. Takeover prediction models can be modified to examine if acquirers are either strategic or financial buyers and, thus, the effects of different types of buyers to takeover likelihood, for instance. Thirdly, feasibility of takeover prediction should be studied in more depth as scholars have not yet reached consensus about the capability to generate abnormal returns with takeover prediction models.

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APPENDICES

Appendix 1. Variable calculation, eliminations and data sources used

Variable	Calculations	Eliminations	Data sources
Market Capitalization[3]	No calculation applied	Less than 10 MEUR dropped	SDC for targets, Datastream for non-targets
Enterprise Value	No calculation applied	No elimination applied (Since, strong correlation with Market Cap)	SDC for targets, Datastream for non-targets
Total Assets	No calculation applied	No elimination applied (Since, strong correlation with Market Cap)	SDC for targets, Datastream for non-targets
Sales	No calculation applied	No elimination applied (Since, strong correlation with Market Cap)	SDC for targets, Datastream for non-targets
P/E	Equity market value / Net Income	Less than -150, higher than 400 dropped	SDC for targets, Datastream for non-targets
P/B	Equity market value / Book value	Less than 0, higher than 50 dropped	SDC for targets, Datastream for non-targets
P/S	Equity market value / Total Sales	Less than 0, higher than 100 dropped	SDC for targets, Datastream for non-targets
EV/EBITDA	Enterprisevalue / EBITDA	Less than -100, higher than 100 dropped	SDC for targets, Datastream for non-targets
Sales Growth % (1y)	($Sales^{t1}$-$Sales^{t0}$) / $Sales^{t0}$	Less than -80%, higher than 4500% dropped	SDC for targets, Datastream for non-targets
ROE	Net Income / Common Equity	Less than -500%, higher than 1000%	SDC for targets, Datastream for non-targets
EBITDA-margin	EBITDA / Sales	Less than -5000%, higher than 5000% dropped	SDC for targets, Datastream for non-targets
Profit-margin	Net Income / Sales	Less than -1000%, higher than 1000 % dropped	SDC for targets, Datastream for non-targets
Asset Turnover	Sales / Total Assets	Higher than 10 dropped	SDC for targets,

			Datastream for non-targets
Operating Cash Flow -margin	Operating cash flow / Sales	Less than -6000%, higher than 5000% dropped	SDC for targets, Datastream for non-targets
Growth-Resource dummy	Dummy=1 if either low growth + high liquidity + low leverage or high growth + low liquidity + high leverage, 0 otherwise	No eliminations applied	SDC for targets, Datastream for non-targets
Leverage	Total debt / Total Assets	Higher than 3500% dropped	SDC for targets, Datastream for non-targets
Gearing	(Total debt – Cash) / Common Equity	Higher than 5000% dropped	SDC for targets, Datastream for non-targets
Cash to Total Assets (Liquidity)	Cash / Total Assets	Higher than 100% dropped	SDC for targets, Datastream for non-targets
Current Ratio	Current Assets / Current Liabilities	Higher than 20 dropped	SDC for targets, Datastream for non-targets
Capex-margin	Capital expenditures / Sales	Higher than 100% dropped	SDC for targets, Datastream for non-targets
Industry dummy	Dummy=1 if M&A activity in given industry previous year, otherwise 0	No eliminations applied	SDC for targets, Datastream for non-targets
GDP dummy	Dummy=1 if GDP growth has a positive value in a given year, otherwise 0	No eliminations applied	World Bank

Appendix 2. Descriptive statistics (STATA)

Estimation section’s 1

targets

```
. summarize if Targetdummy==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Targetdummy	577	1	0	1	1
MARKETCAPI~N	577	1694333	5743489	10000	8.18e+07
LNMARKETCAP	577	12.97643	1.497792	9.21034	18.2201
ENTERPRISE~E	577	3286986	2.00e+07	45008	4.44e+08
LNEV	577	13.33201	1.531372	10.7146	19.91148
NETSALES	577	1870166	9269555	885	2.03e+08
LNNETSALES	577	12.93904	1.63548	6.785588	19.12704
TOTALASSETS	577	2185619	8784228	1600	1.63e+08
LNTOTALASS~S	577	13.08862	1.613108	7.377759	18.91173
PE	577	24.71716	65.97321	-150	400
PB	577	3.404815	5.380934	0	50
PS	577	2.352796	7.109214	.0098311	100
EVEBITDA	577	13.41192	21.87386	-100	100
SalesGrowth	577	.2611813	1.451306	-.5624387	24.5433
ROE	577	.071569	.44559	-5	4.4124
ProfitMargin	577	.0272052	.2118022	-1	1
EBITDAMargin	577	.0924774	.4737043	-5	3.138884
OperatingC~n	577	.0825265	.4230887	-5.88098	3.781318
AssetTurno~r	577	1.109839	.7724273	.015136	7.698665
Gearing	577	.4774426	2.092311	-13.31517	15
CurrentRatio	577	1.71382	1.352393	0	20
Cashtotota~s	577	.1435336	.1503701	0	.7978805
CapexMargin	577	.0761867	.1540787	-.2003479	1
Leverage	577	.2188434	.203314	0	1.212269
Industrydi~Y	577	.3275563	.4697293	0	1
GRDUMMY	577	.3136915	.4643952	0	1
EBITDA	577	270064.3	1784970	-348300.8	3.94e+07
Macrodummy	577	.897747	.3032437	0	1

Estimation section's non-targets

```
. summarize if Targetdummy==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Targetdummy	13,218	0	0	0	0
MARKETCAPI~N	13,218	2494323	1.04e+07	10007	1.96e+08
LNMARKETCAP	13,218	12.20791	2.005446	9.21104	19.09245
ENTERPRISE~E	13,218	3296601	1.40e+07	10003	2.61e+08
LNEV	13,218	12.40646	2.05131	9.21064	19.37993
NETSALES	13,218	3361989	1.41e+07	790	2.79e+08
LNNETSALES	13,218	12.55873	2.054726	6.672033	19.44668
TOTALASSETS	13,218	4290288	2.10e+07	2088	4.76e+08
LNTOTALASS~S	13,218	12.53883	2.076477	7.643962	19.98065
PE	13,218	16.60582	40.51063	-149.6366	398.6846
PB	13,218	2.417135	2.58077	.0293274	49.23115
PS	13,218	1.261686	2.22738	.0080391	57.99171
EVEBITDA	13,218	7.425241	18.42402	-100	100
SalesGrowth	13,218	.2556002	1.671117	-.8	45
ROE	13,218	.0376739	.3715671	-4.927157	9.02583
ProfitMargin	13,218	.0212086	.1436577	-.9965939	.9787723
EBITDAMargin	13,218	.1091334	.173766	-1.727371	5
OperatingC~n	13,218	.0665897	.166385	-4.127158	3.591117
AssetTurno~r	13,218	1.18414	.6510166	.0095038	8.191705
Gearing	13,218	.5501242	1.130572	-11.09579	14.91581
CurrentRatio	13,218	1.890362	1.484057	0	19.51311
Cashtotota~s	13,218	.0767292	.1013223	0	1.047927
CapexMargin	13,218	.0538275	.0898819	-.0435492	.9815951
Leverage	13,218	.2082945	.1647665	0	2.034661
Industrydi~Y	13,218	.2140263	.4101607	0	1
GRDUMMY	13,218	.2349826	.424004	0	1
EBITDA	13,218	456754.3	2375558	-1.13e+07	5.18e+07
Macrodummy	13,218	.845438	.3615003	0	1

Prediction section's targets

```
. summarize if Targetdummy==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Targetdummy	125	1	0	1	1
MARKETCAPI~N	125	2776881	6243105	17936	4.20e+07
LNMARKETCAP	125	13.36644	1.692725	9.794565	17.55337
ENTERPRISE~E	124	4720387	1.09e+07	48425	6.26e+07
LNEV	124	13.85001	1.700953	10.78777	17.95241
NETSALES	125	2360768	5565374	17	4.51e+07
LNNETSALES	125	12.96291	2.207809	2.833213	17.62429
TOTALASSETS	125	4453990	1.03e+07	14200	6.59e+07
LNTOTALASS~S	125	13.4195	1.983092	9.560997	18.0036
PE	125	16.2568	48.46382	-150	180.7619
PB	125	3.50758	4.439225	0	31.64406
PS	125	4.409136	15.32887	.0672721	100
SalesGrowth	125	.2580425	1.23851	-.7492587	13.03357
ROE	125	.0636408	.5905655	-5	3.9016
ProfitMargin	125	.0033651	.2164112	-1	1
EBITDAMargin	125	.1198338	.23187	-1	.6672519
OperatingC~n	125	.0847864	.2005267	-1.26635	.5380105
AssetTurno~r	125	.9096251	.5954213	.0000163	3.942887
Gearing	125	.2826115	.9191734	-1	5.307021
CurrentRatio	125	1.715628	1.852435	.1225766	16.11111
Cashtotota~s	125	.1485311	.1419549	0	.820937
CapexMargin	125	.0688627	.1297445	0	1
Leverage	125	.2437483	.2053999	0	1.111387
Industrydi~Y	125	.328	.4713741	0	1
GRDUMMY	125	.224	.4185998	0	1
EBITDA	125	420799.5	1153560	-40400	8976500
EVEBITDA	125	14.77903	18.88924	-10.19042	100
Macrodummy	125	1	0	1	1

Prediction section's Non-targets

```
. summarize if Targetdummy==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Targetdummy	3,556	0	0	0	0
MARKETCAPI~N	3,556	4058689	1.36e+07	10063	1.69e+08
LNMARKETCAP	3,556	12.93293	2.094474	9.216621	18.94434
ENTERPRISE~E	3,556	5130547	1.83e+07	10047	2.59e+08
LNEV	3,556	13.11724	2.117352	9.215029	19.37255
NETSALES	3,556	4260889	1.58e+07	743	2.83e+08
LNNETSALES	3,556	12.97187	2.09867	6.610696	19.46166
TOTALASSETS	3,556	5979448	2.69e+07	3548	5.38e+08
LNTOTALASS~S	3,556	13.07522	2.125849	8.174139	20.10332
PE	3,556	19.81977	37.38619	-150	391.6296
PB	3,556	2.899062	2.962275	0	44.64757
PS	3,556	1.696422	2.759304	.0063354	48.20643
SalesGrowth	3,556	.0929608	.8850266	-.8	40
ROE	3,556	.0641305	.3161832	-4.377633	3.899171
ProfitMargin	3,556	.0279174	.1541742	-1	.9401795
EBITDAMargin	3,556	.1183734	.1725665	-1.973687	1.351854
OperatingC~n	3,556	.0773981	.1678023	-2.027358	1.336255
AssetTurno~r	3,556	1.064816	.6036166	.0130892	7.614081
Gearing	3,556	.3796291	.951762	-15	13.52903
CurrentRatio	3,556	1.854876	1.406158	0	18.93135
Cashtotota~s	3,556	.1215564	.1203384	0	.973788
CapexMargin	3,556	.0514355	.0864388	0	.93302
Leverage	3,556	.2117413	.1601356	0	1.187925
Industrydi~Y	3,556	.1757593	.3806688	0	1
GRDUMMY	3,556	.2334083	.4230593	0	1
EBITDA	3,556	569428.4	2405506	-2035314	4.65e+07
EVEBITDA	3,556	10.05888	19.53454	-100	100
Macrodummy	3,556	1	0	1	1

Appendix 3. T-tests (STATA)

Size hypothesis

```
. ttest MARKETCAPITALIZATION, by (Targetdummy)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |  13,218     2494323    90726.55    1.04e+07     2316486     2672160
       1 |     577     1694333    239104.6     5743489     1224709     2163956
---------+--------------------------------------------------------------------
combined |  13,795     2460862    87514.67    1.03e+07     2289321     2632403
---------+--------------------------------------------------------------------
    diff |            799990.5    437114.1               -56812.59     1656794
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =   1.8302
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9664         Pr(|T| > |t|) = 0.0672          Pr(T > t) = 0.0336
```

```
. ttest ENTERPRISEVALUE, by (Targetdummy)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |  13,218     3296601    121605.1    1.40e+07     3058237     3534964
       1 |     577     3286986    832776.6    2.00e+07     1651337     4922636
---------+--------------------------------------------------------------------
combined |  13,795     3296199    121605.3    1.43e+07     3057836     3534562
---------+--------------------------------------------------------------------
    diff |            9614.242    607462.1                -1181094     1200323
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =   0.0158
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.5063         Pr(|T| > |t|) = 0.9874          Pr(T > t) = 0.4937
```

. ttest NETSALES, by (Targetdummy)

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	13,218	3361989	122417.4	1.41e+07	3122034	3601945
1	577	1870166	385896.6	9269555	1112229	2628102
combined	13,795	3299591	118427.7	1.39e+07	3067457	3531726
diff		1491824	591452.6		332496.3	2651151

```
    diff = mean(0) - mean(1)                                      t =   2.5223
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9942         Pr(|T| > |t|) = 0.0117          Pr(T > t) = 0.0058
```

. ttest TOTALASSETS, by (Targetdummy)

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	13,218	4290288	182540.9	2.10e+07	3932481	4648094
1	577	2185619	365692.2	8784228	1467366	2903872
combined	13,795	4202256	175608.6	2.06e+07	3858039	4546473
diff		2104669	877045		385541.4	3823796

```
    diff = mean(0) - mean(1)                                      t =   2.3997
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9918         Pr(|T| > |t|) = 0.0164          Pr(T > t) = 0.0082
```

Valuation hypothesis

. ttest PE, by (Targetdummy)

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	13,218	16.60582	.3523596	40.51063	15.91515	17.2965
1	577	24.71716	2.746501	65.97321	19.32278	30.11154
combined	13,795	16.94509	.3568668	41.91477	16.24559	17.6446
diff		-8.111341	1.781339		-11.60301	-4.619673

```
    diff = mean(0) - mean(1)                                      t =  -4.5535
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

```
. ttest PB, by (Targetdummy)

Two-sample t test with equal variances

   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |  13,218    2.417135    .0224474     2.58077    2.373135    2.461136
       1 |     577    3.404815    .2240112    5.380934    2.964837    3.844793
---------+--------------------------------------------------------------------
combined |  13,795    2.458447    .0235179    2.762233    2.412348    2.504545
---------+--------------------------------------------------------------------
    diff |           -.9876796    .1171792               -1.217367   -.7579924
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  -8.4288
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

```
. ttest PS, by (Targetdummy)

Two-sample t test with equal variances

   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |  13,218    1.261686    .0193736     2.22738    1.223711    1.299662
       1 |     577    2.352796    .2959604    7.109214    1.771503    2.934089
---------+--------------------------------------------------------------------
combined |  13,795    1.307324    .0223839    2.629042    1.263448      1.3512
---------+--------------------------------------------------------------------
    diff |            -1.09111    .1114292               -1.309526   -.8726931
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  -9.7920
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

```
. ttest EVEBITDA, by (Targetdummy)

Two-sample t test with equal variances

   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |  13,218    7.425241    .1602513    18.42402    7.111126    7.739357
       1 |     577    13.41192    .9106207    21.87386    11.62338    15.20046
---------+--------------------------------------------------------------------
combined |  13,795    7.675644    .1585229    18.61885    7.364918    7.986371
---------+--------------------------------------------------------------------
    diff |           -5.986676    .7902362               -7.535647   -4.437706
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  -7.5758
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

Inefficient management hypothesis

```
. ttest SalesGrowth, by (Targetdummy)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |  13,218    .2556002    .0145353    1.671117     .227109    .2840915
       1 |     577    .2611813    .0604186    1.451306    .1425136     .379849
---------+--------------------------------------------------------------------
combined |  13,795    .2558337    .0141544    1.662459    .2280892    .2835781
---------+--------------------------------------------------------------------
    diff |           -.0055811    .0707061               -.1441746    .1330125
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  -0.0789
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.4685         Pr(|T| > |t|) = 0.9371          Pr(T > t) = 0.5315
```

```
. ttest ROE, by (Targetdummy)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |  13,218    .0376739    .0032319    .3715671    .0313389    .0440088
       1 |     577     .071569    .0185502      .44559    .0351348    .1080032
---------+--------------------------------------------------------------------
combined |  13,795    .0390916    .0031928    .3749987    .0328333    .0453499
---------+--------------------------------------------------------------------
    diff |           -.0338951    .0159465               -.0651524   -.0026379
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  -2.1256
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0168         Pr(|T| > |t|) = 0.0336          Pr(T > t) = 0.9832
```

```
. ttest ProfitMargin, by (Targetdummy)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |  13,218    .0212086    .0012495    .1436577    .0187593    .0236578
       1 |     577    .0272052    .0088174    .2118022     .009887    .0445235
---------+--------------------------------------------------------------------
combined |  13,795    .0214594    .0012527    .1471358    .0190039    .0239149
---------+--------------------------------------------------------------------
    diff |           -.0059967    .0062576               -.0182625    .0062691
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  -0.9583
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.1690         Pr(|T| > |t|) = 0.3379          Pr(T > t) = 0.8310
```

```
. ttest EBITDAMargin, by (Targetdummy)

Two-sample t test with equal variances
```

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	13,218	.1091334	.0015114	.173766	.1061708	.112096
1	577	.0924774	.0197206	.4737043	.0537445	.1312104
combined	13,795	.1084368	.0016665	.1957367	.1051701	.1117034
diff		.016656	.0083237		.0003404	.0329715

```
    diff = mean(0) - mean(1)                                      t =   2.0010
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9773         Pr(|T| > |t|) = 0.0454          Pr(T > t) = 0.0227
```

```
. ttest AssetTurnover, by (Targetdummy)

Two-sample t test with equal variances
```

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	13,218	1.18414	.0056625	.6510166	1.173041	1.195239
1	577	1.109839	.0321566	.7724273	1.046681	1.172998
combined	13,795	1.181032	.0055911	.6566809	1.170073	1.191991
diff		.0743009	.0279221		.0195697	.1290321

```
    diff = mean(0) - mean(1)                                      t =   2.6610
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9961         Pr(|T| > |t|) = 0.0078          Pr(T > t) = 0.0039
```

Growth Resource mismatch hypothesis

```
. ttest GRDUMMY, by (Targetdummy)

Two-sample t test with equal variances
```

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	13,218	.2349826	.003688	.424004	.2277537	.2422115
1	577	.3136915	.019333	.4643952	.2757197	.3516633
combined	13,795	.2382747	.0036274	.4260435	.2311646	.2453849
diff		-.0787089	.0181077		-.1142024	-.0432154

```
    diff = mean(0) - mean(1)                                      t =  -4.3467
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

Industry disturbance hypothesis

```
. ttest IndustrydisturbanceDUMMY, by (Targetdummy)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |  13,218    .2140263    .0035676    .4101607    .2070334    .2210193
       1 |     577    .3275563    .0195551    .4697293    .2891484    .3659643
---------+--------------------------------------------------------------------
combined |  13,795    .2187749      .00352    .4134306    .2118753    .2256746
---------+--------------------------------------------------------------------
    diff |            -.11353     .017557                -.1479442   -.0791158
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  -6.4664
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

Cash Flow hypothesis

```
. ttest OperatingCashFlowMargin, by (Targetdummy)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |  13,218    .0665897    .0014472     .166385    .0637529    .0694264
       1 |     577    .0825265    .0176134    .4230887    .0479322    .1171209
---------+--------------------------------------------------------------------
combined |  13,795    .0672563    .0015702    .1844204    .0641785     .070334
---------+--------------------------------------------------------------------
    diff |          -.0159368    .0078424                 -.031309   -.0005646
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  -2.0321
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0211         Pr(|T| > |t|) = 0.0422          Pr(T > t) = 0.9789
```

Indebtedness hypothesis

```
. ttest Leverage, by (Targetdummy)

Two-sample t test with equal variances
```

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	13,218	.2082945	.0014331	.1647665	.2054854	.2111037
1	577	.2188434	.0084641	.203314	.2022192	.2354677
combined	13,795	.2087357	.0014181	.1665622	.205956	.2115155
diff		-.0105489	.0070835		-.0244335	.0033357

```
    diff = mean(0) - mean(1)                                      t =  -1.4892
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0682         Pr(|T| > |t|) = 0.1365          Pr(T > t) = 0.9318
```

```
. ttest Gearing, by (Targetdummy)

Two-sample t test with equal variances
```

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	13,218	.5501242	.0098337	1.130572	.5308488	.5693996
1	577	.4774426	.0871041	2.092311	.3063623	.6485229
combined	13,795	.5470842	.0101018	1.186483	.5272832	.5668852
diff		.0726816	.0504585		-.026224	.1715872

```
    diff = mean(0) - mean(1)                                      t =   1.4404
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9251         Pr(|T| > |t|) = 0.1498          Pr(T > t) = 0.0749
```

Liquidity hypothesis

```
. ttest Cashtototalassets, by (Targetdummy)

Two-sample t test with equal variances
```

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	13,218	.0767292	.0008813	.1013223	.0750018	.0784567
1	577	.1435336	.00626	.1503701	.1312384	.1558288
combined	13,795	.0795234	.0008913	.1046892	.0777763	.0812706
diff		-.0668044	.0044161		-.0754605	-.0581483

```
    diff = mean(0) - mean(1)                                      t = -15.1276
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

```
. ttest CurrentRatio, by (Targetdummy)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |  13,218    1.890362    .0129083    1.484057     1.86506    1.915664
       1 |     577     1.71382    .0563009    1.352393     1.60324      1.8244
---------+--------------------------------------------------------------------
combined |  13,795    1.882978    .0125937    1.479162    1.858292    1.907663
---------+--------------------------------------------------------------------
    diff |            .1765413    .0628923                .0532638    .2998188
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =   2.8070
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9975         Pr(|T| > |t|) = 0.0050          Pr(T > t) = 0.0025
```

Investment behavior hypothesis

```
. ttest CapexMargin, by (Targetdummy)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |  13,218    .0538275    .0007818    .0898819    .0522951    .0553599
       1 |     577    .0761867    .0064144    .1540787    .0635883    .0887852
---------+--------------------------------------------------------------------
combined |  13,795    .0547627    .0007965    .0935531    .0532014     .056324
---------+--------------------------------------------------------------------
    diff |           -.0223592    .0039744               -.0301495   -.014569
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  -5.6259
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

Macroeconomic condition hypothesis

```
. ttest Macrodummy, by (Targetdummy)

Two-sample t test with equal variances
```

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	13,218	.845438	.0031443	.3615003	.8392747	.8516013
1	577	.897747	.0126242	.3032437	.8729519	.922542
combined	13,795	.847626	.0030599	.3593961	.8416281	.8536238
diff		-.0523089	.015279		-.0822578	-.02236

```
    diff = mean(0) - mean(1)                                      t =  -3.4236
Ho: diff = 0                                     degrees of freedom =    13793

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0003         Pr(|T| > |t|) = 0.0006          Pr(T > t) = 0.9997
```

Appendix 4. Correlation matrix (STATA)

```
. pwcorr MARKETCAPITALIZATION ENTERPRISEVALUE NETSALES TOTALASSETS PE PB PS EVEBITDA SalesGrowth ROE ProfitMargin EBITDAMargin
>  AssetTurnover OperatingCashFlowMargin Gearing Leverage CurrentRatio Cashtototalassets CapexMargin IndustrydisturbanceDUMMY
> GRDUMMY Macrodummy, star(0.05) sig
```

	MARKET~N	ENTERP~E	NETSALES	TOTALA~S	PE	PB	PS
MARKETCAPI~N	1.0000						
ENTERPRISE~E	0.9114*	1.0000					
	0.0000						
NETSALES	0.7534*	0.8167*	1.0000				
	0.0000	0.0000					
TOTALASSETS	0.7487*	0.8502*	0.8916*	1.0000			
	0.0000	0.0000	0.0000				
PE	0.0124	0.0050	-0.0085	-0.0065	1.0000		
	0.1467	0.5539	0.3205	0.4451			
PB	0.0494*	0.0171*	-0.0391*	-0.0400*	0.0954*	1.0000	
	0.0000	0.0443	0.0000	0.0000	0.0000		
PS	0.0315*	0.0079	-0.0507*	-0.0330*	0.0778*	0.3884*	1.0000
	0.0002	0.3523	0.0000	0.0001	0.0000	0.0000	
EVEBITDA	0.0204*	0.0278*	-0.0067	-0.0013	0.1835*	0.0945*	0.0316*
	0.0166	0.0011	0.4322	0.8750	0.0000	0.0000	0.0002
SalesGrowth	-0.0141	-0.0139	-0.0186*	-0.0139	-0.0104	0.0565*	0.1061*
	0.0989	0.1019	0.0291	0.1015	0.2237	0.0000	0.0000
ROE	0.0692*	0.0556*	0.0393*	0.0307*	0.1131*	0.0213*	0.0192*
	0.0000	0.0000	0.0000	0.0003	0.0000	0.0122	0.0241
ProfitMargin	0.0885*	0.0693*	0.0307*	0.0329*	0.1500*	0.0437*	-0.0070
	0.0000	0.0000	0.0003	0.0001	0.0000	0.0000	0.4139
EBITDAMargin	0.0991*	0.0874*	0.0335*	0.0505*	0.1137*	0.0298*	-0.0178*
	0.0000	0.0000	0.0001	0.0000	0.0000	0.0005	0.0369
AssetTurno~r	-0.1121*	-0.1223*	-0.0583*	-0.1228*	-0.0203*	0.1063*	-0.2704*
	0.0000	0.0000	0.0000	0.0000	0.0172	0.0000	0.0000
OperatingC~n	0.0908*	0.0812*	0.0361*	0.0505*	0.0859*	-0.0068	-0.0443*
	0.0000	0.0000	0.0000	0.0000	0.0000	0.4223	0.0000
Gearing	0.0126	0.0778*	0.0906*	0.1066*	-0.0358*	0.0191*	-0.1275*
	0.1389	0.0000	0.0000	0.0000	0.0000	0.0252	0.0000

Leverage	0.0102	0.0669*	0.0649*	0.0722*	-0.0411*	-0.1196*	-0.1679*
	0.2331	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
CurrentRatio	-0.0755*	-0.0887*	-0.1021*	-0.0928*	0.0355*	0.0408*	0.3174*
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Cashtotota~s	-0.0202*	-0.0324*	-0.0216*	-0.0327*	0.0051	0.1291*	0.1597*
	0.0175	0.0001	0.0113	0.0001	0.5483	0.0000	0.0000
CapexMargin	0.0294*	0.0390*	0.0132	0.0387*	0.0241*	-0.0308*	0.1409*
	0.0006	0.0000	0.1218	0.0000	0.0047	0.0003	0.0000
Industrydi~Y	-0.0094	-0.0119	-0.0113	-0.0087	0.0014	0.0241*	0.0216*
	0.2691	0.1620	0.1857	0.3070	0.8714	0.0046	0.0113
GRDUMMY	-0.0145	-0.0250*	-0.0299*	-0.0280*	0.0089	0.0199*	0.0107
	0.0886	0.0034	0.0005	0.0010	0.2968	0.0197	0.2078
Macrodummy	0.0249*	0.0201*	0.0024	0.0036	0.0251*	0.0612*	0.0398*
	0.0034	0.0183	0.7787	0.6708	0.0032	0.0000	0.0000

	EVEBITDA	SalesG~h	ROE	Profit~n	EBITDA~n	AssetT~r	Operat~n
EVEBITDA	1.0000						
SalesGrowth	0.0051	1.0000					
	0.5521						
ROE	0.1236*	0.0028	1.0000				
	0.0000	0.7422					
ProfitMargin	0.1937*	-0.0335*	0.6002*	1.0000			
	0.0000	0.0001	0.0000				
EBITDAMargin	0.1456*	-0.0066	0.3881*	0.6886*	1.0000		
	0.0000	0.4370	0.0000	0.0000			
AssetTurno~r	-0.0156	-0.0361*	0.0606*	0.0194*	-0.1645*	1.0000	
	0.0666	0.0000	0.0000	0.0226	0.0000		
OperatingC~n	0.1177*	-0.0177*	0.2464*	0.4918*	0.5129*	-0.0900*	1.0000
	0.0000	0.0376	0.0000	0.0000	0.0000	0.0000	
Gearing	0.0142	-0.0025	-0.1927*	-0.0844*	0.0213*	-0.0777*	-0.0071
	0.0942	0.7702	0.0000	0.0000	0.0123	0.0000	0.4018
Leverage	0.0256*	-0.0044	-0.1134*	-0.0740*	0.0798*	-0.1749*	0.0261*
	0.0026	0.6071	0.0000	0.0000	0.0000	0.0000	0.0022

CurrentRatio	0.0039	0.0265*	0.0718*	0.0902*	0.0355*	-0.1093*	-0.0338*
	0.6434	0.0019	0.0000	0.0000	0.0000	0.0000	0.0001
Cashtotota~s	-0.0252*	0.0134	0.0369*	0.0202*	-0.0071	-0.0554*	0.0156
	0.0031	0.1168	0.0000	0.0178	0.4053	0.0000	0.0676
CapexMargin	-0.0109	0.0387*	-0.0204*	-0.0133	0.1439*	-0.3135*	0.0832*
	0.1985	0.0000	0.0164	0.1192	0.0000	0.0000	0.0000
Industrydi~Y	0.0101	0.0215*	-0.0199*	-0.0183*	-0.0209*	-0.0154	-0.0102
	0.2366	0.0116	0.0193	0.0319	0.0139	0.0697	0.2331
GRDUMMY	-0.0030	0.0249*	0.0215*	0.0257*	0.0088	0.0084	0.0020
	0.7266	0.0034	0.0116	0.0025	0.3002	0.3248	0.8152
Macrodummy	0.0177*	-0.0035	0.0130	0.0167	0.0203*	-0.0289*	0.0120
	0.0379	0.6820	0.1274	0.0500	0.0170	0.0007	0.1599

	Gearing	Leverage	Curren~o	Cashto~s	CapexM~n	Indust~Y	GRDUMMY
Gearing	1.0000						
Leverage	0.6732*	1.0000					
	0.0000						
CurrentRatio	-0.2376*	-0.3191*	1.0000				
	0.0000	0.0000					
Cashtotota~s	-0.3138*	-0.2479*	0.2742*	1.0000			
	0.0000	0.0000	0.0000				
CapexMargin	0.1016*	0.2178*	-0.0192*	-0.0220*	1.0000		
	0.0000	0.0000	0.0239	0.0098			
Industrydi~Y	0.0018	-0.0224*	0.0239*	0.0186*	-0.0112	1.0000	
	0.8333	0.0086	0.0050	0.0285	0.1884		
GRDUMMY	-0.1533*	-0.1784*	0.1149*	0.3714*	-0.0259*	0.0160	1.0000
	0.0000	0.0000	0.0000	0.0000	0.0023	0.0601	
Macrodummy	-0.0163	-0.0178*	-0.0042	0.0343*	-0.0076	-0.0186*	-0.0209*
	0.0553	0.0361	0.6225	0.0001	0.3727	0.0289	0.0141

	Macrod~y
Macrodummy	1.0000

Appendix 5. VIF-tests (STATA)

. vif

Variable	VIF	1/VIF
ENTERPRISE~E	9.65	0.103576
TOTALASSETS	6.60	0.151446
MARKETCAPI~N	6.36	0.157208
NETSALES	5.47	0.182919
ProfitMargin	2.84	0.352716
EBITDAMargin	2.26	0.441824
Leverage	2.18	0.459719
Gearing	2.08	0.481650
ROE	1.64	0.610175
PS	1.56	0.643032
OperatingC~n	1.46	0.685353
AssetTurno~r	1.40	0.716243
Cashtotota~s	1.36	0.733547
PB	1.36	0.733588
CurrentRatio	1.32	0.760265
CapexMargin	1.19	0.842973
GRDUMMY	1.18	0.845728
EVEBITDA	1.08	0.925009
PE	1.06	0.941413
SalesGrowth	1.02	0.983587
Macrodummy	1.01	0.990547
Industrydi~Y	1.00	0.995867
Mean VIF	2.50	

Appendix 5. Regression models (STATA)

Model I

```
. clogit Targetdummy LNMARKETCAP LNTOTALASSETS PE PB PS EVEBITDA ROE EBITDAMargin AssetTurnover GRDUMMY Indust
> rydisturbanceDUMMY, group(YEARSIC3)
note: multiple positive outcomes within groups encountered.
note: 2,497 groups (8,780 obs) dropped because of all positive or
      all negative outcomes.

Iteration 0:   log likelihood = -1078.0846
Iteration 1:   log likelihood = -1063.1948
Iteration 2:   log likelihood = -1063.1663
Iteration 3:   log likelihood = -1063.1663

Conditional (fixed-effects) logistic regression

                                                Number of obs     =      5,015
                                                LR chi2(11)       =     168.83
                                                Prob > chi2       =     0.0000
Log likelihood = -1063.1663                     Pseudo R2         =     0.0736
```

Targetdummy	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
LNMARKETCAP	.242728	.0823807	2.95	0.003	.0812648	.4041913
LNTOTALASSETS	-.0825415	.0798807	-1.03	0.301	-.2391047	.0740218
PE	.0014682	.0009897	1.48	0.138	-.0004715	.0034079
PB	.0362391	.0166489	2.18	0.030	.0036078	.0688703
PS	.0424603	.0204652	2.07	0.038	.0023492	.0825714
EVEBITDA	.0129651	.0026017	4.98	0.000	.0078658	.0180644
ROE	.1455427	.1481539	0.98	0.326	-.1448336	.435919
EBITDAMargin	-.9685533	.2606705	-3.72	0.000	-1.479458	-.4576486
AssetTurnover	-.1849832	.0905701	-2.04	0.041	-.3624974	-.007469
GRDUMMY	.5176612	.1103592	4.69	0.000	.3013611	.7339612
IndustrydisturbanceDUMMY	.4282847	.1822407	2.35	0.019	.0710996	.7854699

Model II

```
. clogit Targetdummy LNMARKETCAP LNTOTALASSETS PE PB PS EVEBITDA ROE EBITDAMargin AssetTurnover GRDUMMY IndustrydisturbanceDUMMY Op
> eratingCashFlowMargin Leverage Cashtototalassets CurrentRatio CapexMargin, group(YEARSIC3)
note: multiple positive outcomes within groups encountered.
note: 2,497 groups (8,780 obs) dropped because of all positive or
      all negative outcomes.

Iteration 0:   log likelihood = -976.24292
Iteration 1:   log likelihood = -959.19398
Iteration 2:   log likelihood = -959.12509
Iteration 3:   log likelihood = -959.12508

Conditional (fixed-effects) logistic regression

                                                Number of obs     =      5,015
                                                LR chi2(16)       =     376.91
                                                Prob > chi2       =     0.0000
Log likelihood = -959.12508                     Pseudo R2         =     0.1642
```

Targetdummy	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
LNMARKETCAP	.3418384	.1002745	3.41	0.001	.145304	.5383728
LNTOTALASSETS	-.1980654	.0992328	-2.00	0.046	-.3925581	-.0035727
PE	.0011895	.0010525	1.13	0.258	-.0008734	.0032524
PB	-.0021214	.0197625	-0.11	0.915	-.0408553	.0366124
PS	.0558338	.0245634	2.27	0.023	.0076903	.1039772
EVEBITDA	.0147269	.0026939	5.47	0.000	.009447	.0200068
ROE	.1760422	.1407163	1.25	0.211	-.0997568	.4518412
EBITDAMargin	-1.165886	.3209568	-3.63	0.000	-1.79495	-.5368222
AssetTurnover	-.0501248	.0985982	-0.51	0.611	-.2433737	.1431242
GRDUMMY	.117288	.1251673	0.94	0.349	-.1280354	.3626113
IndustrydisturbanceDUMMY	.4687352	.1893651	2.48	0.013	.0975865	.839884
OperatingCashFlowMargin	.4680493	.278843	1.68	0.093	-.078473	1.014572
Leverage	1.069651	.4052862	2.64	0.008	.2753052	1.863998
Cashtototalassets	6.376532	.4909139	12.99	0.000	5.414358	7.338705
CurrentRatio	-.3504055	.0609235	-5.75	0.000	-.4698134	-.2309975
CapexMargin	1.560462	.5108888	3.05	0.002	.5591388	2.561786

Model III

```
. clogit Targetdummy LNMARKETCAP LNTOTALASSETS PE PB PS EVEBITDA ROE EBITDAMargin AssetTurnover GRDUMMY OperatingCashFlowMargin Lev
> erage Cashtototalassets CurrentRatio CapexMargin, group(YEARSIC3)
note: multiple positive outcomes within groups encountered.
note: 2,497 groups (8,780 obs) dropped because of all positive or
      all negative outcomes.

Iteration 0:   log likelihood = -969.57351
Iteration 1:   log likelihood =  -962.2775
Iteration 2:   log likelihood = -962.26584
Iteration 3:   log likelihood = -962.26584

Conditional (fixed-effects) logistic regression

                                                Number of obs     =      5,015
                                                LR chi2(15)       =     370.63
                                                Prob > chi2       =     0.0000
Log likelihood = -962.26584                     Pseudo R2         =     0.1615
```

Targetdummy	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
LNMARKETCAP	.336254	.1002374	3.35	0.001	.1397923	.5327156
LNTOTALASSETS	-.1935841	.0992809	-1.95	0.051	-.3881712	.0010029
PE	.0012088	.0010547	1.15	0.252	-.0008585	.003276
PB	-.0001573	.0196959	-0.01	0.994	-.0387605	.0384459
PS	.0562435	.0249715	2.25	0.024	.0073003	.1051866
EVEBITDA	.014773	.0026988	5.47	0.000	.0094834	.0200626
ROE	.160275	.137271	1.17	0.243	-.1087713	.4293213
EBITDAMargin	-1.135703	.318552	-3.57	0.000	-1.760054	-.5113529
AssetTurnover	-.0573687	.0987851	-0.58	0.561	-.250984	.1362466
GRDUMMY	.1237076	.1250477	0.99	0.323	-.1213813	.3687966
OperatingCashFlowMargin	.4656153	.2779388	1.68	0.094	-.0791347	1.010365
Leverage	1.054224	.4047341	2.60	0.009	.2609593	1.847488
Cashtototalassets	6.369976	.4897772	13.01	0.000	5.41003	7.329922
CurrentRatio	-.3478578	.0610925	-5.69	0.000	-.4675968	-.2281188
CapexMargin	1.507998	.5073737	2.97	0.003	.5135638	2.502432

Model IV

```
. clogit Targetdummy LNMARKETCAP LNTOTALASSETS PE PB PS EVEBITDA ROE EBITDAMargin AssetTurnover GRDUMMY OperatingCashFlowMargin Lev
> erage Cashtototalassets CurrentRatio CapexMargin, group(YEARSIC4)
note: multiple positive outcomes within groups encountered.
note: 4,659 groups (10,733 obs) dropped because of all positive or
      all negative outcomes.

Iteration 0:   log likelihood = -628.27759
Iteration 1:   log likelihood = -622.59412
Iteration 2:   log likelihood = -622.58169
Iteration 3:   log likelihood = -622.58169

Conditional (fixed-effects) logistic regression

                                                Number of obs     =      3,062
                                                LR chi2(15)       =     325.83
                                                Prob > chi2       =     0.0000
Log likelihood = -622.58169                     Pseudo R2         =     0.2074
```

Targetdummy	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
LNMARKETCAP	.3757846	.1181388	3.18	0.001	.1442368	.6073323
LNTOTALASSETS	-.1949267	.1159821	-1.68	0.093	-.4222474	.032394
PE	.0006508	.0012652	0.51	0.607	-.0018289	.0031304
PB	.006158	.0225375	0.27	0.785	-.0380147	.0503307
PS	.0690704	.0280027	2.47	0.014	.0141861	.1239548
EVEBITDA	.0133175	.0030967	4.30	0.000	.007248	.019387
ROE	.2091339	.182285	1.15	0.251	-.1481381	.5664059
EBITDAMargin	-.8815912	.346038	-2.55	0.011	-1.559813	-.2033691
AssetTurnover	-.0610941	.1113402	-0.55	0.583	-.2793169	.1571286
GRDUMMY	.1964938	.1457782	1.35	0.178	-.0892262	.4822139
OperatingCashFlowMargin	.3827256	.3064259	1.25	0.212	-.2178581	.9833093
Leverage	.7018538	.4653869	1.51	0.132	-.2102878	1.613995
Cashtototalassets	6.750002	.5921784	11.40	0.000	5.589354	7.91065
CurrentRatio	-.4176716	.0725054	-5.76	0.000	-.5597797	-.2755636
CapexMargin	1.411575	.5566148	2.54	0.011	.3206303	2.50252

Model V

```
. logistic Targetdummy LNMARKETCAP LNTOTALASSETS PE PB PS EVEBITDA ROE EBITDAMargin AssetTurnover GRDUMMY IndustrydisturbanceDUMMY,
>  coef
```

```
Logistic regression                             Number of obs     =     13,795
                                                LR chi2(11)       =     248.34
                                                Prob > chi2       =     0.0000
Log likelihood = -2272.1153                     Pseudo R2         =     0.0518
```

Targetdummy	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
LNMARKETCAP	.1499624	.0642114	2.34	0.020	.0241104	.2758143
LNTOTALASSETS	.0277649	.0623929	0.45	0.656	-.094523	.1500528
PE	.0017535	.0008507	2.06	0.039	.0000863	.0034208
PB	.0411811	.0131955	3.12	0.002	.0153183	.0670438
PS	.0393697	.0131025	3.00	0.003	.0136894	.0650501
EVEBITDA	.0134501	.0021548	6.24	0.000	.0092268	.0176734
ROE	.1727749	.1313415	1.32	0.188	-.0846498	.4301995
EBITDAMargin	-.7959048	.1951312	-4.08	0.000	-1.178355	-.4134548
AssetTurnover	-.0506652	.0757367	-0.67	0.504	-.1991064	.097776
GRDUMMY	.4084691	.0943958	4.33	0.000	.2234567	.5934815
IndustrydisturbanceDUMMY	.5764334	.0928911	6.21	0.000	.3943703	.7584966
_cons	-5.857508	.3155017	-18.57	0.000	-6.47588	-5.239136

Model VI

```
. logistic Targetdummy LNMARKETCAP LNTOTALASSETS PE PB PS EVEBITDA ROE EBITDAMargin AssetTurnover GRDUMMY OperatingCashFlowMargin L
> everage CurrentRatio Cashtototalassets CapexMargin, coef
```

```
Logistic regression                             Number of obs     =     13,795
                                                LR chi2(15)       =     431.85
                                                Prob > chi2       =     0.0000
Log likelihood = -2180.3631                     Pseudo R2         =     0.0901
```

Targetdummy	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
LNMARKETCAP	.2699853	.0751802	3.59	0.000	.1226348	.4173358
LNTOTALASSETS	-.1089398	.0750666	-1.45	0.147	-.2560676	.0381879
PE	.0019245	.000865	2.22	0.026	.0002291	.0036198
PB	-.0057132	.0158569	-0.36	0.719	-.0367922	.0253657
PS	.0577784	.0153526	3.76	0.000	.0276878	.0878689
EVEBITDA	.0151665	.0021946	6.91	0.000	.0108651	.0194679
ROE	.1799426	.132702	1.36	0.175	-.0801485	.4400337
EBITDAMargin	-.8932417	.2365186	-3.78	0.000	-1.35681	-.4296738
AssetTurnover	.1234888	.0784222	1.57	0.115	-.0302159	.2771935
GRDUMMY	.1493645	.1031951	1.45	0.148	-.0528942	.3516233
OperatingCashFlowMargin	.2378553	.2067553	1.15	0.250	-.1673776	.6430883
Leverage	1.217072	.3174299	3.83	0.000	.5949203	1.839223
CurrentRatio	-.3100756	.0490845	-6.32	0.000	-.4062795	-.2138718
Cashtototalassets	4.997179	.3576232	13.97	0.000	4.29625	5.698108
CapexMargin	1.435534	.372364	3.86	0.000	.7057144	2.165354
_cons	-5.843598	.370907	-15.75	0.000	-6.570562	-5.116633

Model VII

```
. logistic Targetdummy LNMARKETCAP LNTOTALASSETS PE PB PS EVEBITDA ROE EBITDAMargin AssetTurnover GRDUMMY OperatingCashFlowMargin L
> everage CurrentRatio Cashtototalassets CapexMargin IndustrydisturbanceDUMMY, coef
```

```
Logistic regression                             Number of obs     =     13,795
                                                LR chi2(16)       =     468.11
                                                Prob > chi2       =     0.0000
Log likelihood = -2162.2307                     Pseudo R2         =     0.0977
```

Targetdummy	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
LNMARKETCAP	.2775009	.0754592	3.68	0.000	.1296037	.4253981
LNTOTALASSETS	-.1120263	.0751526	-1.49	0.136	-.2593227	.0352701
PE	.0018918	.0008664	2.18	0.029	.0001936	.00359
PB	-.0092812	.0160499	-0.58	0.563	-.0407385	.0221761
PS	.0588378	.0152281	3.86	0.000	.0289912	.0886844
EVEBITDA	.0149866	.0022121	6.77	0.000	.0106509	.0193223
ROE	.1998104	.1335789	1.50	0.135	-.0619995	.4616202
EBITDAMargin	-.8610825	.2396137	-3.59	0.000	-1.330717	-.3914482
AssetTurnover	.135755	.0783855	1.73	0.083	-.0178777	.2893878
GRDUMMY	.1412209	.1033878	1.37	0.172	-.0614154	.3438573
OperatingCashFlowMargin	.2045537	.2078425	0.98	0.325	-.2028101	.6119175
Leverage	1.239824	.3170272	3.91	0.000	.6184618	1.861185
CurrentRatio	-.3129786	.0490303	-6.38	0.000	-.4090762	-.216881
Cashtototalassets	5.000586	.3599705	13.89	0.000	4.295057	5.706115
CapexMargin	1.47912	.3741222	3.95	0.000	.7458543	2.212386
IndustrydisturbanceDUMMY	.5889898	.0947423	6.22	0.000	.4032983	.7746813
_cons	-6.062035	.3737209	-16.22	0.000	-6.794514	-5.329555

Model VIII

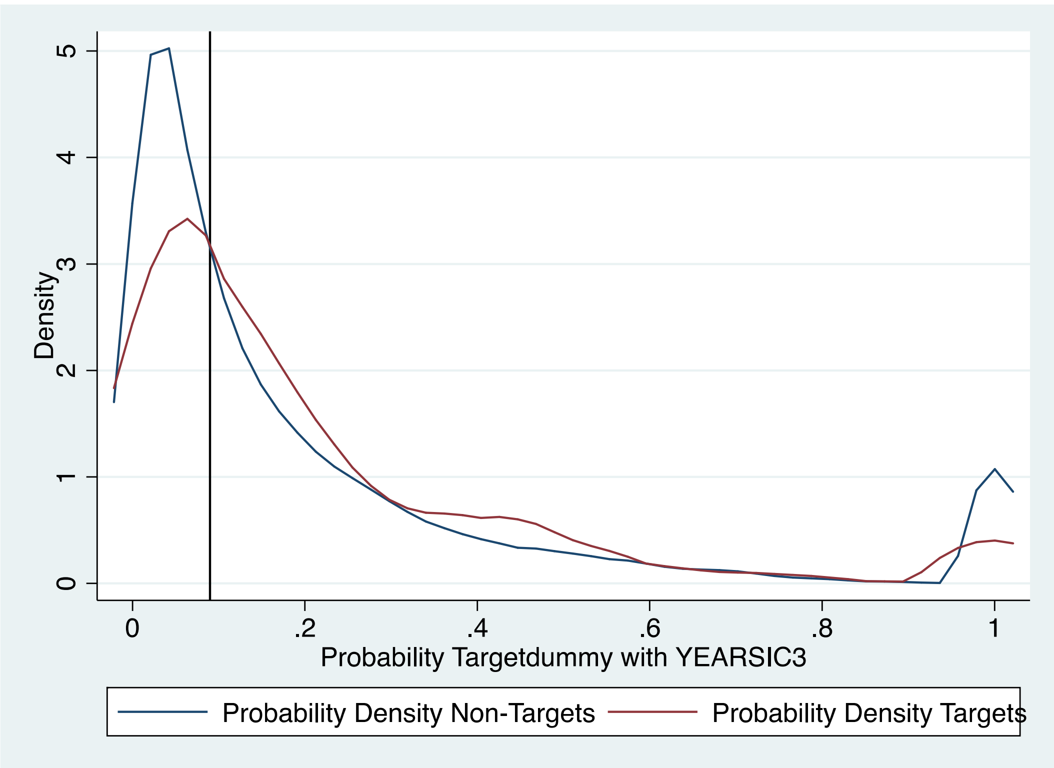
```
. logistic Targetdummy LNMARKETCAP LNTOTALASSETS PE PB PS EVEBITDA ROE EBITDAMargin AssetTurnover GRDUMMY OperatingCashFlowMargin L
> everage CurrentRatio Cashtototalassets CapexMargin IndustrydisturbanceDUMMY Macrodummy, coef

Logistic regression                             Number of obs     =     13,795
                                                LR chi2(17)       =     475.56
                                                Prob > chi2       =     0.0000
Log likelihood = -2158.5048                     Pseudo R2         =     0.0992
```

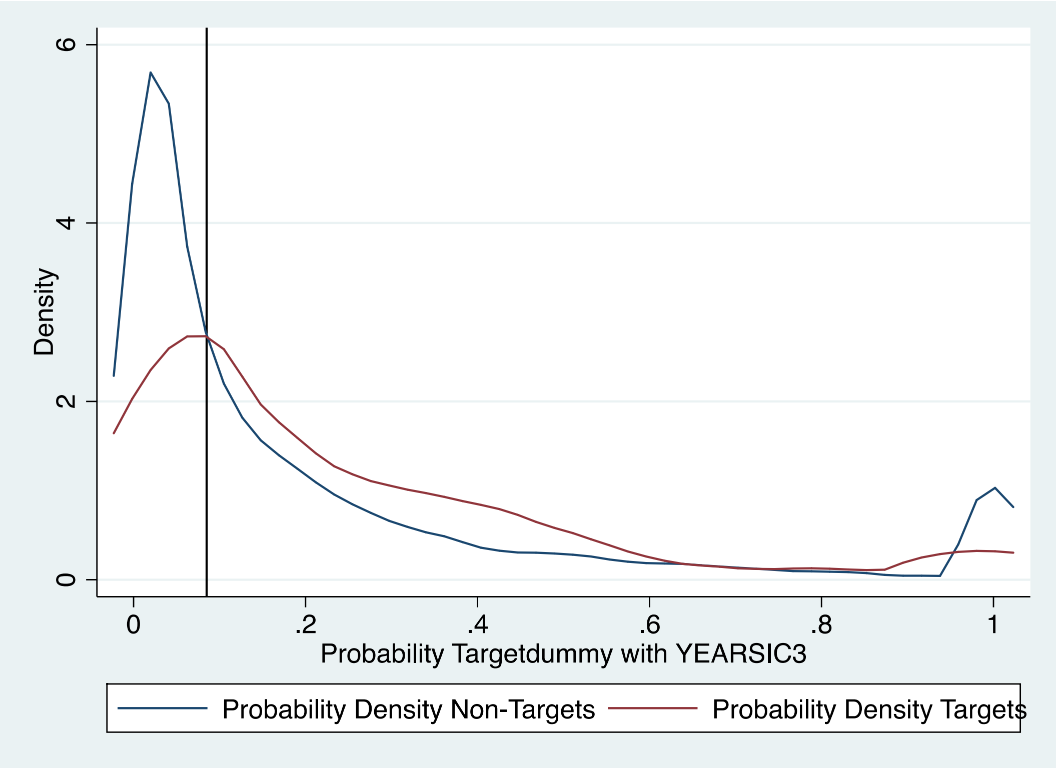
Targetdummy	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
LNMARKETCAP	.2587366	.0757551	3.42	0.001	.1102593	.4072139
LNTOTALASSETS	-.0949268	.0753824	-1.26	0.208	-.2426735	.0528199
PE	.0018554	.0008651	2.14	0.032	.0001598	.003551
PB	-.0082214	.0161609	-0.51	0.611	-.0398962	.0234535
PS	.0591984	.0149137	3.97	0.000	.0299681	.0884286
EVEBITDA	.0150139	.0022112	6.79	0.000	.01068	.0193478
ROE	.2011	.1328869	1.51	0.130	-.0593535	.4615534
EBITDAMargin	-.8851627	.2406067	-3.68	0.000	-1.356743	-.4135823
AssetTurnover	.1407696	.0782277	1.80	0.072	-.012554	.2940931
GRDUMMY	.1508839	.1035259	1.46	0.145	-.0520232	.353791
OperatingCashFlowMargin	.2202275	.2078361	1.06	0.289	-.1871239	.6275789
Leverage	1.218849	.3174112	3.84	0.000	.5967346	1.840964
CurrentRatio	-.3103366	.0490352	-6.33	0.000	-.4064438	-.2142295
Cashtototalassets	4.967205	.3600805	13.79	0.000	4.26146	5.67295
CapexMargin	1.510143	.3734847	4.04	0.000	.7781263	2.242159
IndustrydisturbanceDUMMY	.5932793	.0947704	6.26	0.000	.4075327	.7790259
Macrodummy	.3791109	.1449575	2.62	0.009	.0949996	.6632223
_cons	-6.386628	.3946658	-16.18	0.000	-7.160159	-5.613097

Appendix 6. Cut-off values

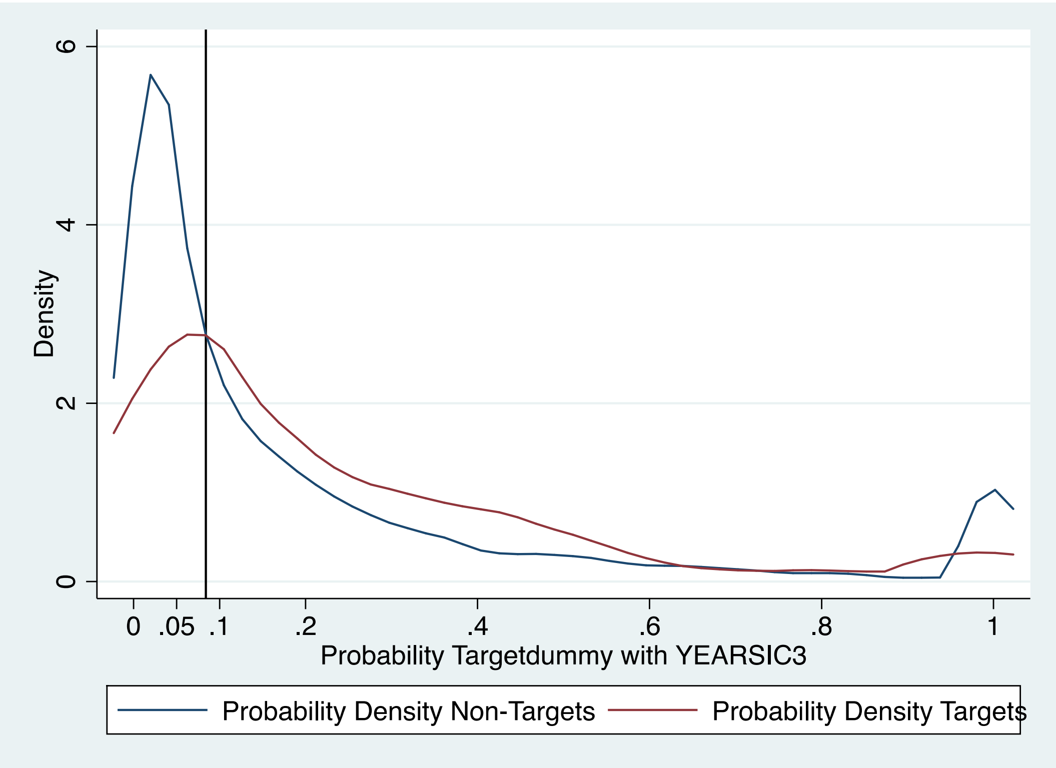
Model I (Cut-off 0.09)



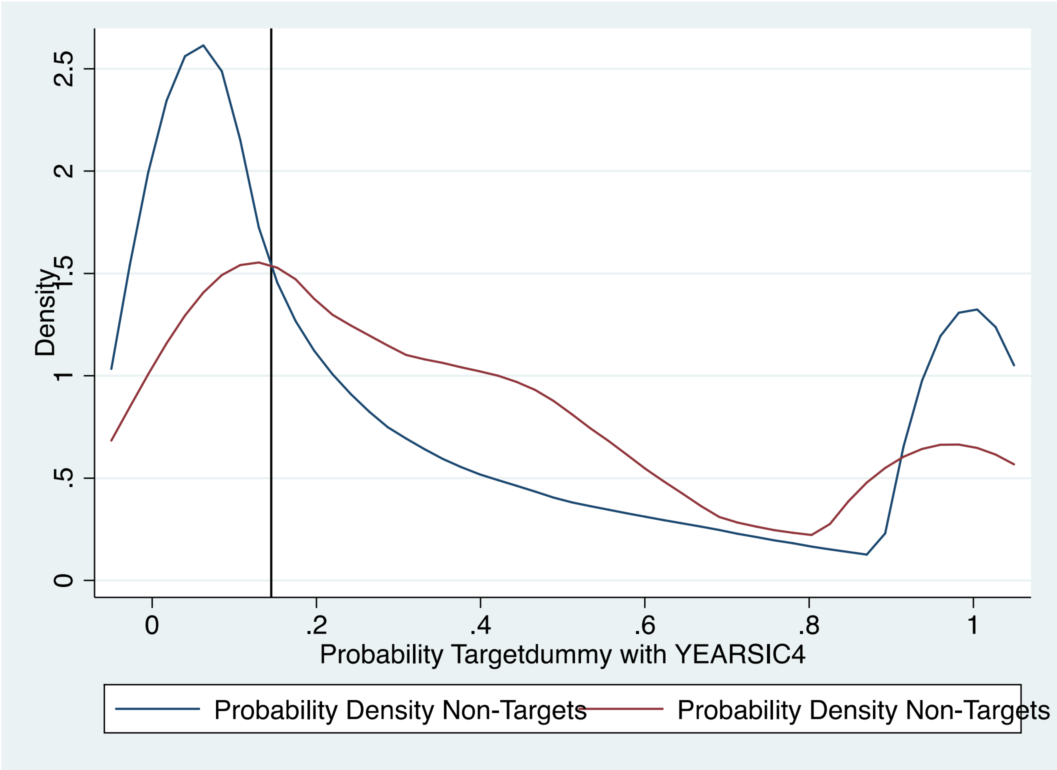
Model II (Cut-off 0.085)



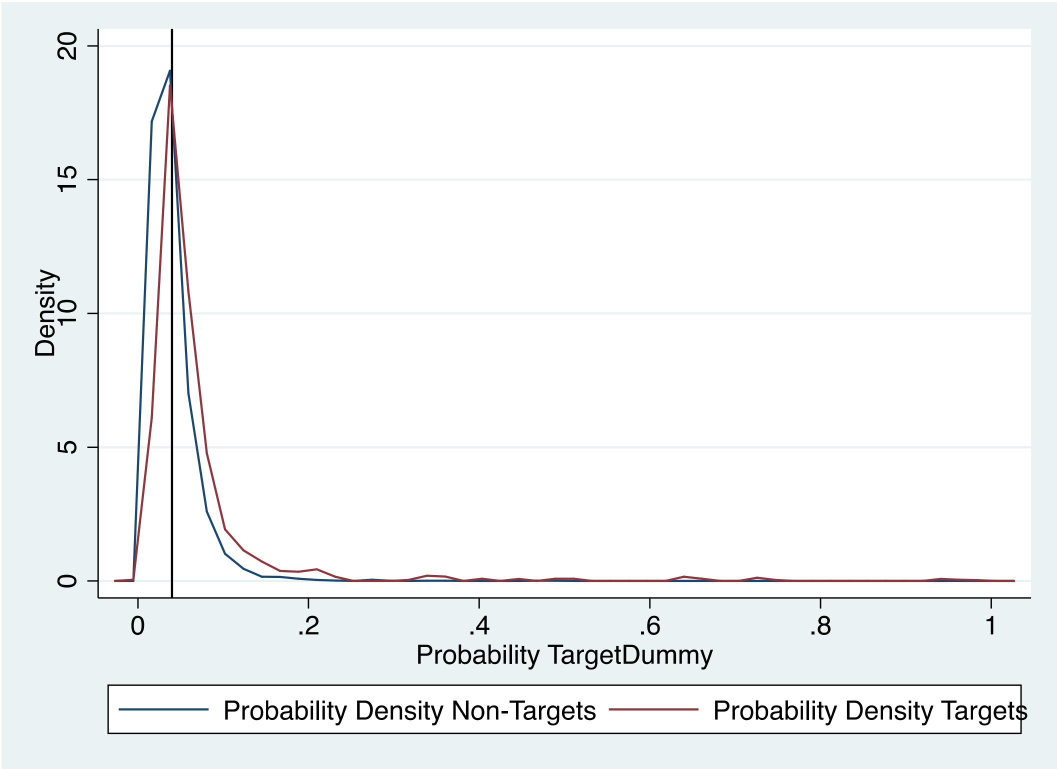
Model III (Cut-off 0.0825)



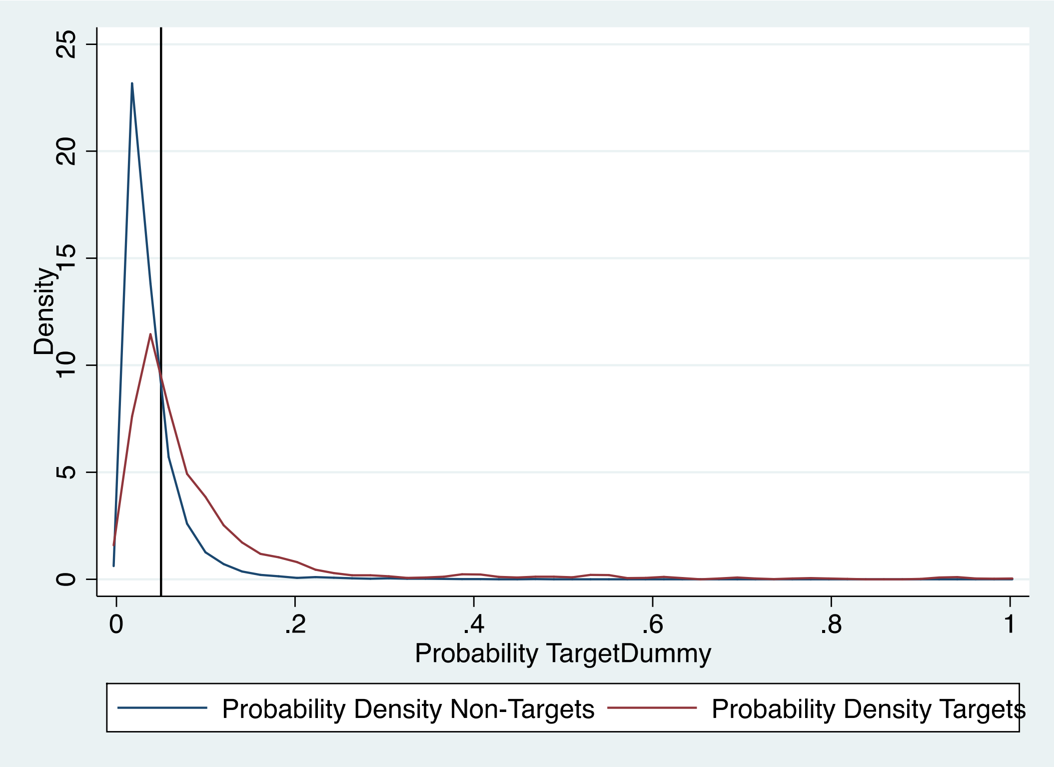
Model IV (Cut-off 0.1450)



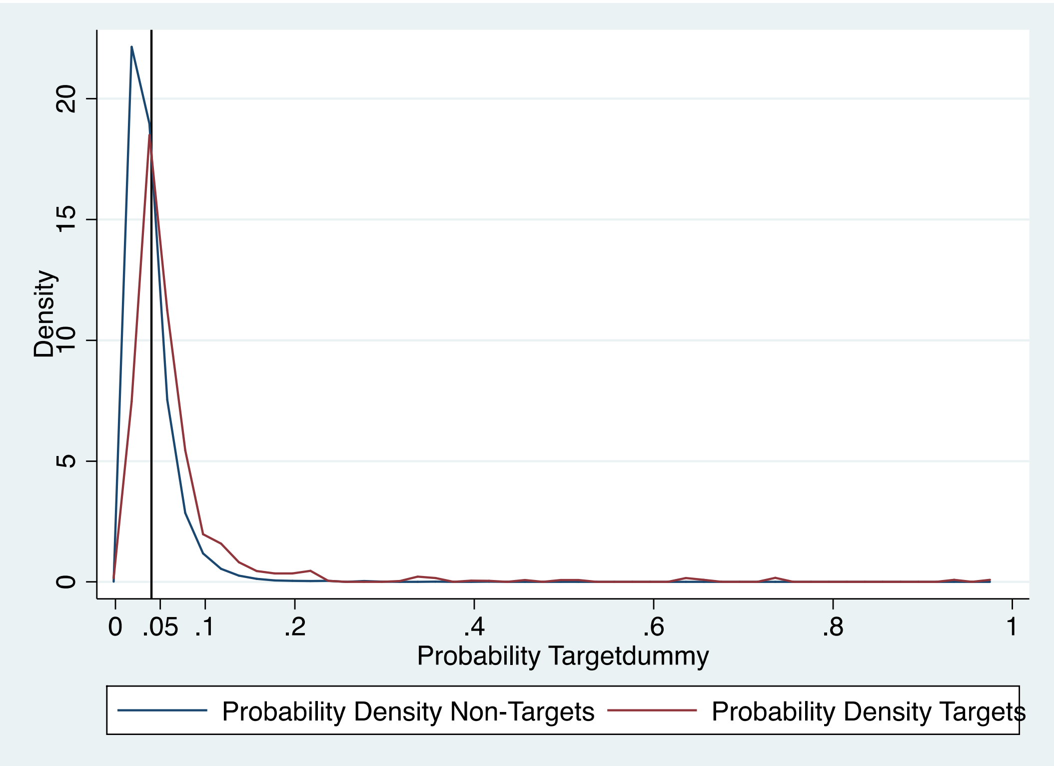
Model V (Cut-off 0.04)



Model VI (Cut-off 0.05)



Model VII (Cut-off 0.04)



Model VIII (Cut-off 0.049)