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Predicting Takeover Targets in the US Technology Industry

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Predicting Takeover Targets in the US Technology Industry

An empirical analysis of the US technology industry

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Abstract

This thesis explores which factors affect takeover prediction in the US technology industry and whether abnormal returns are achievable with an investment portfolio based on takeover probabilities. With a sample consisting of 581 target- and 2130 non-target observations from the period 1993-2014, the takeover prediction probabilities are calculated through a logistic regression model. Incorporating the fifth and sixth merger waves in a model focusing solely on the US technology industry is new to this field of research. The results from the logistic regression indicate that (increases in) Revenue Growth along with the Current Ratio and Debt/Assets have a significantly negative impact on takeover probability, while (increases in) the Natural Logarithm of Revenue, Dividend Yield, Fed Rate and Industry Disturbances have a significantly positive impact on takeover probability. The estimates are applied on a hold-out sample consisting of 145 target- and 675 non-target observations over the period 2015-2018 to form two investment portfolios. The portfolio formed by the minimum misclassification-strategy (Palepu, 1986) achieves 2.06% abnormal return over the period, predicting 27.54% of the targets and 84.31% of the non-targets correctly. The portfolio formed according to the maximum target-strategy (Powell, 2001) achieves –5.32% abnormal return over the period, predicting 83.33% of the targets and 83.79% of the non-targets correctly. Thus, the results suggest that one can predict takeover targets quite accurately, though there are limitations to the extent to which one can achieve abnormal returns from it. This provides an exciting basis for future extensions and utilization of the industry-specific takeover prediction model.

Key words: Takeover prediction, logistic regression, abnormal return, investing strategy, technology, market efficiency

JEL classification: O51, L63, L65, C53, G11, G14, G34

Preface

This thesis was written as the final paper of our MSc. in Business at the BI Norwegian Business School, and we would very much like to extend our sincere gratitude towards the individuals whom have contributed to realizing it.

First and foremost, we would like to thank our supervisor associate professor Leon Bogdan Stacescu for sharing his extensive knowledge in the field of *Corporate Finance* and his generous guidance, continuous inputs and constructive criticism throughout the writing of this thesis.

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Oslo, Norway, July 1st, 2019

Vegard Høivik Enok Voll

Vegard Høivik Enok Voll

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List of abbreviations and acronyms

AR	Abnormal return
CAR	Cumulative abnormal return
CAAR	Cumulative average abnormal return
CAPEX	Capital expenditure
C-ratio	Concentration – Ratio
CR	Current Ratio
CRSP	The Center for Research in Security Prices
D/A	Debt/Assets
D/E	Debt/Equity
DGCL	Delaware General Corporation Law
FED	Federal Reserve (rate)
FRED	Federal Reserve Research Division
GAAP	Generally Accepted Accounting Principles
GDP	Gross Domestic Product
GRMM	Growth-Resource Mismatch (dummy)
IFRS	International Financial Reporting Standards
ID	Identification
IndDist	Industry Disturbance Dummy
IPO	Initial Public Offering
M&A	Mergers & Acquisitions
M/B	Market value/Book value

NAICS	North American Industry Classification System
NBA	Net Book Assets
LBO	Leveraged Buy-Out
LnRev	The Natural Logarithm of Annual Revenue
OLS	Ordinary Least Squares
P/E	Price/Earnings
P/IAE	Price/Innovation-Adjusted-Earnings
PM	Profit Margin
PRR	Price Research Ratio
R	Return
R^2	R-squared
R&D	Research & Development
ROE	Return on Equity
ROIC	Return on Invested Capital
SDC	Securities Data Company Platinum
SEC	Security and Exchange Commission
SIC	Standard Industry Classification
S&P	Standard & Poor
UK	United Kingdom (of Great Britain)
Unemp	Unemployment (rate)
US	United States (of America)

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1. Introduction

M&A's are in general terms used to describe the consolidation of companies or assets through various types of financial transactions. These events are thoroughly researched in financial markets with statistical models using publicly available information, and it is well documented that the majority of target shareholders receive significant premiums from these transactions. Under the efficient market hypothesis (EMH), where share prices reflect all information, investors should not be able to achieve abnormal returns. However, industries subject to fundamental changes[1] are more likely to be inefficient at times of disruption, leading investors to the idea of predicting takeover targets for investment opportunities. This means investors should be able to generate abnormal returns if their prediction model displays the takeover likelihood more accurately than the market's assessment of it. Hence, this thesis will test the proficiency of such a prediction model and determine whether the EMH holds in the US technology industry ("tech-industry").

In order to predict takeover targets, a model that differentiates targets from non-targets is needed. Palepu (1986) suggested the use of a logistic regression model and tested the predicted probabilities' ability to form a successful investment strategy by classifying observations as targets or non-targets, using a cut-off derived from the *minimum misclassification*-strategy. He proceeded to suggest six hypotheses to explain the variation in takeover probability and estimated takeover probabilities with the logistic regression model. By investing in the firms classified as targets and holding their stock for 250 trading days, the resulting portfolio yielded a statistically insignificant cumulative abnormal return (CAR) of –1.6%.

Palepu's strategy for classifying takeover targets by minimizing misclassifications has in more recent literature been sidelined by Powell's (2001) strategy of maximizing the number of targets in the investment portfolio, arguing that the gains from additional targets outweigh the cost of possible misclassification. By investing

[1] Industries such as: technology, taxi, real estate, pharmaceuticals etc.

in the firms classified as targets through the *maximum targets*-strategy, Powell's portfolio generated a statistically significant CAR of –11.0%.

Most recent empirical studies[2] on takeover prediction are based on Palepu's paradigm paired with Powell's methodology of investment, and the consensus appears to be that the model is able to predict targets to some degree of accuracy when paired with appropriate independent variables, and to create a profitable investment strategy. However, the mixed methodologies and results of prior studies imply there is room for improvements.

Following the learnings of Palepu (1986) and Powell (2001), this thesis' main research question is to explore whether investors can achieve abnormal returns on the basis of estimated takeover probabilities for firms in the US technology industry (tech-industry). The prediction model is built on data from 2711 observations (581 targets, 2130 non-targets) between 1993-2014 and applied on a hold-out sample of 820 observations (145 targets, 675 non-targets) between 2015-2018. Ergo, this sample constitutes a period and an industry previously not explored in a takeover prediction study.

The main results on predicting targets are coherent with prior studies, indicating that poorly performing firms with liquidity issues are more likely to become targets. The results regarding firm size are however incoherent with prior studies, suggesting that firm size is positively correlated with takeover likelihood, i.e. that acquirers prefer firms with a proven ability to grow, rather than investing in firms with unrealized growth potential. There is no evidence for a relationship between R&D-expenditures and takeover likelihood in the US tech-industry, and the evidence for a relationship between the *Fed rate* and takeover likelihood is opposite of what was expected,

[2] Ambrose & Megginson, 1992; Barnes, 1990/1999; Powell, 2001/2004; Brar, Giamouridis & Liodakis, 2009; Cremers, Nair & John, 2009.

indicating that takeovers cluster when the economy is prospering (high *Fed rate*) rather than stagnating (low *Fed rate*).

By applying the *minimum misclassification*- and *maximum target*-strategies separately in two annually rebalanced investment portfolios, the resulting CARs are 2.06% and -5.32%, respectively. Albeit insignificantly different from zero, the predictive accuracy of the *maximum target*-portfolio (83.33% for targets, 83.79% for non-targets) is superior to that of most antecedent studies. The findings of the study indicate that investors can quite accurately predict takeover targets in the US tech-industry, though achieving abnormal returns from it seems improbable. Thus, this study finds that the EMH holds with regards to the market's assessment of takeover probabilities in the US tech-industry.

1.1 Purpose, Contribution & Layout

The thesis' purpose is to assess whether the EMH holds in the US tech-industry by applying Palepu's (1986) takeover prediction model and *minimum misclassification*-strategy, and Powell's (2001) *maximum targets*-strategy. This is done by using well-known factors as well as a set of new industry-specific factors considered relevant for the industry. Thus, this thesis contributes to existing literature by expanding on the hypotheses suggested in previous studies and by introducing a new industry-specific hypothesis to explore the application of prediction models on single industries. Moreover, as the tech-industry is recognized as a highly disruptive and dynamic environment compared to other large industries, there is a higher chance that the tech-industry is inefficient. If so, the spectrum in which abnormal returns are attainable with a prediction model increases. Consequently, the thesis aims to deepen the academic insight on the application of prediction models in general and broaden the insight by applying it on a single industry.

Furthermore, this thesis contributes to the existing literature on the financial composition of tech-firms over the sample period and thereby also highlights which attributes distinguish attractive from unattractive tech-firms in the eyes of investors and acquirers.

The layout of the paper is as follows: Chapter 2 presents an overview of the empirical evidence from existing literature. Chapter 3 presents the hypotheses needed to empirically investigate whether the EMH holds in the US tech-industry. Chapter 4 describes the data used for the analysis, while Chapter 5 presents the analysis' methodology. Chapter 6 shows the empirical results and Chapter 7 concludes the paper, discusses limitations and adds suggestions for further research.

2. Literature review

The literature review is presented in two parts. Chapter 2.1 presents previous empirical studies and frameworks in accordance with their publication, relevance and development. Chapter 2.2 reviews the relevant literature on abnormal returns from takeovers and takeover prediction.

2.1 Prediction of Takeover Targets

There has been a number of studies on predicting takeover targets using publicly available information, and most of the studies are conducted on the basis of potential abnormal returns, as target shareholders tend to earn substantial abnormal returns around the time of the takeover announcement.

However, the market does not show any documented effects of predictive power earlier than two months prior to takeover announcement (Schwert, 1996; Eckbo, 2009), and Jensen and Ruback (1983) claim that it is borderline impossible for the market to identify future takeover targets. This implies that if a model has predictive power of potential takeover targets, it should give investors the possibility to earn positive market adjusted returns by acquiring these targets earlier than two months prior to the announcement of the takeover.

2.1.1 Prior studies

As mentioned, several studies have been conducted on this topic, and most studies have been conducted on the US market (Dietrich & Sorensen (1984), Palepu (1986), Ambrose & Megginson (1992) and Cremers, Nair and John (2009)) and the European/UK market: Barnes (1990;1999), Powell (1997;2001;2004), Brar et al. (2009), Froese (2013) and Khan & Myrholt (2018), by means of various methodologies.

Harris, Stewart, Guilkey and Carleton (1982) applied a probit model to distinguish characteristics of potential takeover targets, while Stevens (1973) and Barnes (1990) applied multiple-discriminant analysis to differentiate targets from non-targets, before Dietrich and Sorensen (1984) applied logistic regression analysis to predict takeover targets after seeing this method applied to predict bankruptcies.

Logistic regressions have the advantage that they are able to classify and differentiate targets from non-targets, with the additional benefit that it also quantifies a probability for a given outcome, here: a firm’s takeover likelihood. Palepu’s (1986) study is one of the more influential studies on the subject, and have later become the basis for several studies on takeover prediction. His study also pointed out several methodological errors of previous empirical studies done by his peers, including the proper use of cut-off probabilities.

2.1.2 Palepu (1986)

In the peer review-portion of Palepu’s paper, he pointed out several methodological errors in prior empirical studies that claimed to have a predictive accuracy of 60-90%. Palepu claimed that previous studies contain three different methodological faults. Firstly, the use of non-random equal share samples leads to biased results, and secondly that equal share samples in prediction tests derive deceptive estimates when attempting to explain the prediction model for takeovers. Lastly, and most importantly, he criticized the use of arbitrary cut-off probabilities when distinguishing between targets and non-targets.

To correct for the flaws, Palepu applied the logistic regression model to distinguish targets from non-targets with a predefined cut-off probability. He suggested deriving the cut-off probability as the intersection between the probability density functions of takeover probability for targets and non-targets. He claimed that this would generate a higher portfolio return through the minimization of misclassifications. Palepu also criticized several previous studies on takeover prediction on the basis of using integrated variables from step-by-step testing a large number of variables for significance, rather than using pre-specified ones. He claimed that this then leads to a statistical overfitting of a model to the sample and further that this is not a “clean” method of building a general explanatory model that explains takeover probability.

Palepu proceeded to suggest nine independent variables to derive the takeover likelihood based on six hypotheses divided into two sub-sections: firm-specific and industry-specific hypotheses.

2.1.2.1 Firm-specific hypotheses

The inefficient management hypothesis was first introduced by Jensen and Ruback (1983) and later hypothesized by Palepu (1986), as he based this hypothesis on the financial theory premise that acquisitions are a mechanism by which managers of a firm failing to maximize its market value are replaced. This was incorporated in the model by adding ROE and the average excess return on the share performance of the firm, as proxies for the quality of management. This hypothesis is used, or built upon, in near all empirical studies on the subject.

The (firm) size hypothesis argues that as the size of the firm increases, a takeover becomes less likely. This implies that smaller firms are more likely to be targets, as there is assumed to be a negative correlation between firm size and takeover probability. Palepu justified the claim by arguing that as post-merger- and takeover defense-costs rise with target size, the number of potential acquiring firms decreases.

The growth-resource mismatch hypothesis implies that there are two kinds of targets likely for a takeover: high-growth/low-resource firms and low-growth/high-resource firms. Palepu hypothesized this relationship and integrated it into his model with a dummy-variable indicating the presence of a growth/resource-imbalance in a firm.

The Market/Book hypothesis argues that firms whose market values are low compared to their book values are likely targets for acquisition because firms with low M*arket/Book ratios* are perceived to be undervalued, as empirically proven by Rhodes-Kropf, Robinson and Viswanathan (2005).

The P/E hypothesis claims that firms with low *P/E-ratio* are likely targets for acquisitions, and Palepu argued that the popularity of the *P/E*-ratio is the real reason he included it in his study, as he deemed the ratio's economic logic questionable.

2.1.2.2 Industry-specific hypotheses

The industry disturbance hypothesis claims that firms in an industry that are subjected to "economic disturbances" are likely targets for acquisitions. Palepu claimed that this hypothesis was derived from Gort's (1969) "economic disturbance theory": that merger rates vary in observation across both time and industry. Mitchell and Mulherin (1996) also assumed that economic shocks influence the aggregated merger activity in an industry. Palepu therefore included an industry dummy-variable indicating takeovers in the same industry during the year prior to the announcement date to account for this hypothesis.

These six hypotheses form the basis of most modern empirical studies on takeover prediction. However, since Palepu's study in 1986, there has been a growing body of research expanding on the subject with additional hypotheses and variables.

2.1.3 Brar, Giamouridis and Liodakis (2009)

Several studies have suggested testing for *leverage* and *liquidity*, to distinguish targets from non-targets. Aforementioned Dietrich and Sorensen (1984) and Brar et al. (2009) tried to implement *leverage* into their empirical studies, but deemed it insignificant. However, Brar et al. (2009) found liquidity to be significantly lower for targets with strong linkage to LBO-firms[3] than for non-targets. They justified their finding by arguing that *cash-to-total assets* is significantly lower for targets than non-targets. They also argued that financially distressed firms are more likely to be targets, but their variables were insignificant.

Brar et al. (2009) also examined the effect of behavioral factors that could be influenced by irrational decisions. They particularly looked at market sentiment with a dummy-variable of value (1) if "*the S&P/Citigroup European Broad Market index (BMI) had a positive total return for 12 months immediately prior to the month of acquisition*", which proved to have an insignificant impact on takeover activity.

2.1.4 Industry-specific factors

Innovation is said to be the heart of technology, and it is fundamental to the business strategy of most firms in the tech-industry. The cornerstone of innovative strength is research and development (R&D), and tech-companies lead the way in R&D-spending (FactSet, 2017).

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[3] Firms acquired through a *leveraged buy-out* (LBO)

A fork in the road when relating R&D-expenses with takeover activity is whether or not R&D-expenditures should be treated as an incurred expense[4] in the same fiscal year (GAAP), or as an investment capitalized[5] over its economic life (IFRS). Domestic US firms are obliged to follow GAAP, while foreign SEC registrants are allowed to follow IFRS. The accounting method has significant implications, e.g. that if R&D is accounted as an operating expense it could lead to great volatility in profit and return calculations as R&D-expenditures can vary annually, or if accounted for as an investment, significantly impact return on invested capital (ROIC). In the July-August issue of HBR (2016), Sherman & Young argued that the results under GAAP vs. IFRS can be significant enough to change an acquisition decision.

One theory popularized by GM Phillips (2012) on key drivers of M&A in the tech-industry is that large firms may find it disadvantageous to engage in a R&D-race with small firms, as large firms can obtain access to innovation through acquisitions while small firms decide to innovate more in order be acquired by larger firms. Furthermore, several studies have been conducted on the subject of market reactions to R&D-expenditures (Griliches, 1981; Wooldridge,1988; Chan et al. 1990), based on the idea that R&D is a source of intangible capital, and most have reported a positive correlation between R&D expenditures and market value of firms (Griliches, 1981; Woolridge, 1988; Johnson and Pazderka, 1993).

Additionally, Szücs (2013) suggested that takeover targets are chosen on the basis of being highly innovative firms, indicated by above average pre-merger R&D intensity[6] for medium-sized targets, and well above average for smaller targets. This supports the conjecture that these firms, and especially smaller firms, have not yet been able to capitalize on their innovative efforts.

[4] Operating expense on the income statement
[5] Asset on the balance sheet
[6] R&D-intensity = R&D/Revenue

2.1.5 Macroeconomic factors

Evidence of mergers and acquisitions happening in waves implies that macroeconomic factors, both behavioral[7] and neoclassical[8], impact takeovers. Bruner (2004) claimed that M&A activity, in addition to firm- and industry-specific factors, is generally affected by macroeconomic conditions, e.g. GDP, interest- and exchange rates. Melicher, Ledolter and D'Antonio (1983) found a weak positive correlation between M&A activity and the macroeconomic situation, while Becketti (1986) found that one third of M&A activity variations in the US between the 60's and 80's could be explained by macroeconomic factors.

Shiller (1988) claimed that mass behavior in financial markets affects the likelihood of takeovers, since aggregated takeover activity triggers further takeover activity due to firms taking advantage of being over- or underpriced. Rhodes-Kropf, Robinson and Viswanathan (2005) argued that a high Market/Book ratio aligns with merger waves, since the Market/Book ratio is a proxy for market overvaluation and that M&A-activity is motivated by investor's valuation errors.

Ploncheck and Sushka (1987) found a negative correlation between the unemployment rate and M&A-activity, while Golbe & White (1988) found evidence that both an increasing GDP and an expanding economy have a positive influence on aggregated takeover activity in US samples, and that interest rates are negatively correlated.

The hypotheses above lay the foundation for the hypotheses used to develop a prediction model (see Chapter 3). Table 1 provides an overview of the main hypotheses, the corresponding variables, the expected signs and their literary origin. For the full list of hypotheses and variables, see Table C1 in Appendix C.

[7] Behavioral economics is primarily concerned with the bounds of rationality of economic agents
[8] Neoclassical economics is an approach to economics that relates supply and demand to an individual's rationality and his or her ability to maximize utility or profit

Table 1 - Summary of main hypotheses and variables from previous studies

A summary of the main hypotheses proposed in former studies on takeover prediction, as well as the statistical significance of the variables and their expected signs.

Hypotheses	Variables	Expected sign	Study
Inefficient management	- Return on equity	Neg.	- Palepu (1986) - Brar, Giamouridis & Liodakis (2009)
	- Profit margin & growth** - Sales growth*	Neg.	- Brar, Giamouridis & Liodakis (2009) - Palepu (1986)
Firm size	- Net book assets	Neg.	- Palepu (1986) - Ambrose & Megginson (1992) - Powell (2001)
	- Market capitalization**	Neg.	- Barnes (1999) - Cremers, Nair & John (2009) - Brar, Giamouridis & Liodakis (2009)
	- Sales*** - No. Of employees	Neg.	- Brar, Giamouridis & Liodakis (2009)
Growth-resource mismatch	- Growth-resource dummy based on sales growth, liquidity and leverage	Pos.	- Palepu (1986) - Ambrose & Megginson (1992) - Powell (2001;2004)
Undervaluation	- Price / Earnings***	Neg.	- Dietrich & Sorensen (1984) - Ambrose & Megginson (1992) - Brar, Giamouridis & Liodakis (2009)
	- Market / Book	Neg.	- Palepu (1986) - Ambrose & Megginson (1992) - Powell (2001)
	- Dividend yield*** - Price /Book	Pos. / Neg.	- Brar, Giamouridis & Liodakis (2009)
Leverage	- Debt / Assets		- Cremers, Nair & John (2009) - Brar, Giamouridis & Liodakis (2009)
	- Debt / Equity	Pos.	- Brar, Giamouridis & Liodakis (2009)
Liquidity	- Cash-to-capital***	Neg.	- Brar, Giamouridis & Liodakis (2009)

* indicates statistical significance at the 10% level
** indicates statistical significance at the 5% level
*** indicates statistical significance at the 1% level

2.2 Abnormal returns from target prediction

The underlying assumption when developing investment strategies for predicted takeover targets is that there are significant positive abnormal returns to the target's shareholders around the time of announcement. In the following chapter, the relevant literature on abnormal returns from takeovers and takeover prediction is reviewed.

2.2.1 Announcement returns

The level of takeover activity has been steadily increasing since the 1960s (Sudarsanam and Mahate, 2003), and the research literature has increased along with it. The consensus appears to be clear: target shareholders in the US and Europe receive significant CAR[9] during takeover announcement. Dodd and Warner's (1983) study of hostile takeovers, or so-called proxy contests, received a 1.2% CAR in the event window (-1, 0), and suggested that near all pre-announcement abnormal returns (5.2%) are received in the run-up (-9,0). Jarell and Poulsen's (1989) US-study received 28.99% in the event window (-20, +10), while Georgen and Renneboog's (2004) study on Continental Europe/UK received 23.10% and 21.66% in the event windows (-40, 0) during the period 1993 - 2000 and (-60, +60) in the period 1962 - 1978, respectively.

Kohers and Kohers (2000) extended on previous studies by examining the abnormal wealth-effects for shareholders in mergers and takeovers of high-tech companies, as opposed to low-tech firms which experience normalized average returns from takeovers. Kohers & Kohers studied the value creation in the short run to shareholders, for the event windows [-1, 0] and [-7, 0], and concluded that there is a wealth gain (+37.89% and +37.41%, respectively). See Table 2 for an overview of empirical studies on abnormal returns to target shareholders.

[9] Defined as the sum of differences between the expected and actual returns within an event window

Table 2 - Cumulative Abnormal Returns (CAR) for target shareholders
Overview of some empirical studies on abnormal returns to target shareholders with variable holding periods and observations.

Study	CAR to shareholders	Study Period and Holding Period in days	Observations	Other information
Dodd & Warner (1983)	+ 1.2% **	1962 - 1978 [-1 , 0]	87	- Hostile takeovers - Observations from the US
Jarell & Poulsen (1989)	+ 28.99% ***	1963 - 1986 [-20 , +10]	526	- Observations from the US
Kohers & Kohers (2000)	37.89%***	1987 - 1996 [-1, 0]	226	- Acquisitioins in high-tech industries
	37.41% ***	1987 - 1996 [-7, 0]	226	- Acquisitioins in high-tech industries
Goergen & Renneboog (2004)	+ 23.10% ***	1993 - 2000 [-40 , 0]	136	- Observations from Europe - Separates UK from Continental Europe
	+ 21.66% ***	1962-1978 [-60 , +60]	136	

*indicates statistical significance at the 10% level
** indicates statistical significance at the 5% level
*** indicates statistical significance at the 1% level

2.2.2 Portfolio returns

As suggested in Chapter 2.2.1, target shareholders can earn significant abnormal returns from a takeover in the short-term time frame around announcement to the public. Palepu (1986) argued that, under the assumption of an efficient market, a model which successfully predicts takeover targets is only able to generate abnormal returns if the predictive power of the model surpasses the market assessment of the firms’ takeover probability at the time of prediction. However, as suggested by Dodd and Ruback (1977), the pre-takeover stock price movement of target firms is rarely accurately predicted by the stock market even three months prior to announcement.

Palepu (1986) conducted the first widely acknowledged study attempting to generate abnormal returns by investing in predicted takeover targets. Out of 1117 observations, his model nominated 625 as targets for the hold-out sample test, where 30 of them were actual targets. Even though his model predicted 80% of the 30 targets correctly, only 45% of the actual non-targets were correctly predicted, indicating a large Type II error in the results.

In this study, Type I errors are when firms are misclassified as targets by the prediction model and Type II errors are when firms are wrongly classified as non-targets. Recent studies (Powell, 2001; Brar et al., 2009) argued that there is a trade-off between Type I and Type II errors when determining the cut-off. Palepu (1986) was of the opinion that the cost of Type I and Type II errors remains equal and constant, and hence aimed to minimize the number of misclassifications in his study. Palepu formed an equally weighted portfolio with his predicted targets, which then generated an excess return of -1.62% over the course of 250 trading days. However, the target portfolio was actually outperformed by the non-target portfolio, which generated an excess return of -1.51%.

On the other hand, Powell (2001) claimed that abnormal returns from investing in targets are larger than the potential costs of investing in non-targets and therefore a model that maximizes target accuracy is preferable to Palepu's *minimum misclassification*-strategy. It is worth noting that the sub-group of 24 actual targets that were included in Palepu's portfolio of predicted targets generated a significant CAR of 20.98%, which speaks to the point made by Powell (2001). With this in mind, Powell (2001) proposed to determine the cut-off probability by splitting the firms in the dataset into deciles based on their estimated takeover probability, and then invest in the decile with the highest takeover probabilities. Thus, Powell (2001) proposed setting the cut-off probability as the lowest probability within the decile with the highest concentration ratio (C-ratio) of targets. Despite making several adaptations in his study, the market-adjusted return of his investment portfolio yielded -11%, even lower than the returns made by Palepu's (1986) *minimum misclassification*-strategy. Furthermore, the size-adjusted model in Powell (2001) generated an insignificant –4.00% CAR.

In a later study, Powell (2004) used the same data as in his 2001-paper, but in a multinomial model, where he predicted only hostile takeovers. This model generated an abnormal return of 7% over a 12-month holding period, with a portfolio consisting of 7 targets and 110 non-targets. However, the non-target firms generated the abnormal return, which was explained by Powell to be due to the larger size of the hostile targets, which was hypothesized to decrease the probability of financial distress compared to friendly targets.

Brar et al. (2009) followed the advice from Powell (2001; 2004) when determining the cut-off probability and constructed a portfolio of the predicted target firms over a 12- month period, with monthly rebalancing. This investment strategy generated an abnormal market-adjusted return of 8.5% relative to a size-matched control portfolio. See Table 3 for an overview of empirical studies on abnormal returns from takeover prediction.

Table 3 - Cumulative Abnormal Returns (CAR) from takeover predictions
Overview of some empirical studies on abnormal returns from takeover prediction with an integrated investment strategy.

Study	CAR on portfolio	Holding period	Other information
Palepu (1986)	- 1.62%	250 days	Investment portfolio consists of 625 predicted targets from a total of 117 firms
Powell (2001)	- 11.0% ***	1 year	Investment portfolio consists of 216 predicted targets from a total of 1000 firms
Powell (2004)	+ 7.0%	1 year	Investment portfolio consists of 117 predicted targets from a total of 1000 firms
Brar, Giamouridis & Liodakis (2009)	+ 8.5 % **	1 month	Investment portfolio of the estimated top 10% most likely takeover targets, porttfolio rebalances on a monthly basis
Cremers, Nair & John (2009)	+ 11.77% *** + 21.67% ***	1 year	Takeover-spread portfolios, buying the quintile/decile with highest estimated takeover likelihood and selling the lowest.

* indicates statistical significance at the 10% level
** indicates statistical significance at the 5% level
*** indicates statistical significance at the 1% level

3. Hypotheses

The basis for developing a takeover prediction model using publicly available information to form a successful investment strategy, rests on the underlying assumption that the target shareholders experience abnormal returns during takeovers. Consequently, this paper empirically investigates whether or not takeover-announcements yield abnormal returns for target shareholders, before developing a takeover-prediction model based on several hypotheses frequently suggested in academic and financial literature. The predictions from this model then serve as the basis for forming an investment strategy. The hypotheses, and the variables derived from them, are discussed below.

The hypotheses are presented in two parts. Chapter 3.1 presents the hypothesis regarding abnormal return to shareholders from takeovers. Chapter 3.2 describes the three general hypotheses (firm-specific, industry-specific and macroeconomic) and the specific hypotheses, as well as their corresponding variables and literary origin.

3.1 Hypothesis - Takeover returns

CAR from takeovers are widely researched across markets, and evidence of significant positive CAR for target shareholders during takeovers are found across event windows and geographical areas. Consequently, and in accordance with previous literature, the following null hypothesis is examined:

> *H0: No significant positive CAR from t days*[10] *prior to t days post announcement date*

As target shareholders' abnormal returns are affected by the choice of event window, the hypotheses are tested over multiple event windows. Following Schwert (1996) and Eckbo (2009) who argued that there is no significant run-up prior to two months

[10] The "*t*" indicates selected event windows

before the takeover announcement, both short and long event windows are tested. Longer event windows allow the model to capture leaks[11] in both the pre- and post-windows, while consequently increasing the risk of including noise. Shorter event windows isolate the short-term announcement effect but fail to display the effect of run-up returns and potential insider trading and information leakage.

3.2 Hypotheses - Takeover predictions

Based on the aforementioned literature, ten hypotheses are formed. The variables derived from the hypotheses are to be included in the takeover prediction model and the hypotheses are categorized into *firm-specific, industry-specific* and *macroeconomic factors.*

3.2.1 Firm-specific hypotheses

1) *Inefficient management:* Underperforming firms are more likely to be acquired

This hypothesis is based on Manne's (1965) theory, and Jensen and Ruback's (1983) later model of management competition, which argued that underperforming managements are replaced by superior value-adding managers as a disciplinary action.

The variables to test for this hypothesis: *Return on equity (ROE)* and *2-year revenue growth* as proxies for the success of the management of a firm, in accordance with Palepu (1986) and Brar et al. (2009), respectively.

2) *Firm size:* Smaller firms are more likely to be acquired

This hypothesis tests the assumption that the likelihood of a takeover decreases with

[11] Insider trading and information leakage

the size of the firm, as a negative correlation between firm size and takeover probability has been suggested in several papers (Palepu, 1986; Brar et al., 2009).

The variables to test for this hypothesis: *Net book assets (NBA)* and *the natural logarithm of revenue in year (t)*, in accordance with Palepu (1986) and Khan and Myrholt (2018), respectively.

3) *Growth - Resource mismatch:* Firms with a mismatch between growth opportunities and financial resources increase the probability of being acquired

This hypothesis implies that there are two types of firms that are likely targets; *high-growth/low-resource* firms and *low-growth/high-resource* firms. The former, being a common financial belief, is arguing that firms with low growth opportunities, but rich in financial resources, are likely targets. The latter, which is suggested in financial literature on asymmetric information, argues that firms with high growth opportunities but insufficient financial resources to fund the growth are also likely targets (Myers and Majluf, 1984).

The variables to test for this hypothesis: A dummy-variable, indicating (1) if the firms are either *low-growth/resource-rich* or *high-growth/resource-poor* and (0) otherwise, in accordance with Palepu (1986), Barnes (1999) and Brar et al. (2009). High/low are dictated by higher/lower than the population average.

4) *Undervaluation:* Firms with low Market/Book and Price/Earnings valuations are more likely to be acquired.

This hypothesis tests the widespread assumption that firms with low Market/Book ratios are "cheap" buys, and thus likely to be acquired. The economic validity of this assumption is somewhat suspect however, as the book value of a firm need not reflect the replacement value of its assets (Levisohn, 2010).

Also the hypothesis tests another popular assumption, that firms with low P/E ratios are likely targets for acquisitions, also due to somewhat questionable economical intuition; that bidders with high P/E ratios seek to acquire firms with low P/E ratios to realize an "instantaneous capital gain" due to the belief that the stock market values the earnings of the combination at the higher P/E ratio of the bidder.

The variables to test for this hypothesis: *Market/Book ratio*, defined as the market value of common equity divided by its book value, *P/E ratio* - defined as: Market Capitalization divided by Net Income, and *Dividend Yield.* The former two are included in several studies, Palepu (1986), Ambrose & Meggison (1992) and Froese (2013), while the latter was later included by Brar et al. (2009).

5) *Leverage:* Firms with high leverage are more likely to be acquired

This hypothesis tests the assumption that financially distressed companies with high levels of debt are more likely to be acquired, indicating that there is a positive correlation between leverage and takeover probability.

The variables to test for this hypothesis: *Debt-to-Equity ratio* and *Debt-to-Assets*, in accordance with Brar et al. (2009) and Cremers, Nair & John (2009).

6) *Liquidity:* Firms with low liquidity are more likely to be acquired

This hypothesis tests the assumption that firms with low liquidity/weak short-term financial capabilities may be financially distressed or unable to realize profitable investment opportunities, and thus not able to maximize shareholder value. Consequently, this attracts acquirers with the financial capabilities to realize such investment opportunities.

The variables to test for this hypothesis: *Current ratio*, as a proxy for short-term robustness, in accordance with Froese (2013) and *cash-to-capital* as a proxy for the firm's ability to take on profitable investment opportunities, in accordance with Brar et al. (2009).

3.2.2 Industry-specific hypotheses

> 7) *Industry disturbance:* Firms affected by an industry shock are more likely to be acquired

This hypothesis tests Gort's (1969) "economic disturbance theory", i.e. that economic shocks trigger takeovers within an industry, as hypothesized by Palepu (1986). Industry disturbance is measured with a dummy variable, indicating (1) if there has been a takeover in the same sub-sector in the 12 months prior to the takeover, and (0) otherwise.

The variable to test for this hypothesis: *IndDistDummy*, in accordance with Palepu (1986).

> 8) *Tech-factors: R&D-focused* firms are more likely to be acquired

This hypothesis tests the assumption that R&D is a key driver for M&A activity, i.e. that firms investing in R&D are more likely to be targets. First, the hypothesis tests if firms with high Price-to-Research (PRR) ratios are more likely targets, i.e. how much a firm spends on R&D compared to its market cap. Second, the hypothesis tests if firms with high Price-to-Innovation-Adjusted Earnings (P/IAE) are more likely targets, i.e. a variation of the P/E ratio which considers R&D spending. Third, the hypothesis tests if firms with high R&D-intensity are more likely targets, i.e. the level of R&D-expenditures in regards to revenue.

The variables to test for this hypothesis: *RDgrowth*, *PriceResearch-ratio*, *P/IAE* and *R&D-intensity*.

3.2.3 Macroeconomic hypotheses

> 9) *Macroeconomic factors:* Acquisitions are more likely when the economic environment supports merger activity

This hypothesis tests the assumption that macroeconomic factors influence the aggregated level of M&A activity, i.e. that firms are more likely to be targets in years with a deal friendly environment. Firstly, the popular assumption that low interest rates increase the likelihood of takeovers is tested, i.e. that there is negative correlation between takeover activity and interest rate. Secondly, that an expanding economy increases the likelihood of takeovers, i.e. that GDP positively influences the aggregated takeover activity. Thirdly, that the employment rate positively influences takeover activity, i.e. that the unemployment rate is negatively correlated with takeover activity.

The variables to test for these hypotheses: *10Y US Treasury Constant Maturity Rate (DGS10/FED)* as included in several studies; Becketti (1986), Ploncheck and Sushka (1987), Yagli (1996) and Globe and White (1998), *GDP* as included in Golbe & White (1988), and *US Unemployment rate (Unemp)* in accordance with Ploncheck and Sushka (1987).

> 10) *Market sentiment:* Firms with target-characteristics are not likely to be acquired due to poor market and economic sentiment

This hypothesis tests Brar, Giamouridis and Liodakis’ (2009) theory of market sentiment, i.e. that a firm which possesses all the characteristics of being a takeover target is unlikely to be one, due to poor market and economic sentiment. Market sentiment is measured with a dummy variable indicating (1) if NASDAQ had a positive total return in the 12 months leading up to the takeover announcement, and (0) otherwise.

The variable to test for this hypothesis: *NasdaqDummy*, in accordance with Brar et al. (2009).

4. Data

As no one database contains all required financial, economic and deal-related data needed for this study, multiple datasets were constructed to hold all necessary information. The primary dataset, consisting of financial data, deal-related information and various identifiers, were obtained from Bloomberg, Compustat and SDC Platinum. The secondary data set, consisting of stock prices, both ex-ante and ex-post to announcement dates, were obtained from CRSP, while the tertiary data set consisting of macro variables were obtained from FRED.

4.1 Takeover announcement returns

The data includes US publicly traded firms in the tech sector, and only from the subsectors of hardware, software, semiconductors and health-technology, gathered by various identifiers (Tickers, SIC and NAICS) in the sample-period of 1993 – 2018. The sample period is set on the basis of data availability and to include the fifth and sixth merger waves.

The majority of US corporations are situated in the state of Delaware due to the bi-partisan political consensus to keep Delaware law modern and up-to-date, and its high-quality corporate courts and judges (Black, 2007). Consequently, most of the M&A-activity is also based in Delaware. Therefore, for deals to be included in this study, they need to meet certain requirements from Delaware law and legislation, in addition to US Federal law.

US federal law dictates through the Exchange Act that when 5% or more of a company's outstanding shares are acquired, it must be disclosed to the public, and the Delaware Code (DGCL) dictates that the threshold for a tender offer is triggered by the acquisition of 50% or more of the shares with voting rights (IFLR, 2013)[12]. Hence, this study disregards acquisitions when less than 5% of voting rights are

[12] Reduced from 90% to 50% in 2013 (IFLR, 2013)

acquired and deals which fail to secure more than 50% ownership ex-post, as no change of control is necessarily represented by these acquisitions.

Target stock prices are collected in the period of 170 trading-days ex-ante announcement to 100 trading-days ex-post announcement from the CRSP-database. This includes the estimation window for the beta calculation prior to takeover announcement and the event windows surrounding the announcement date. The stock prices are subsequently used for the event study and the calculation of CAAR.

Furthermore, Nasdaq Composite prices are collected from FRED to be used as a proxy for market returns in order to assess the abnormal returns of the takeover targets.

4.2 Predicting takeover targets

The estimation sample is a pooled sample of successfully acquired targets, and non-targets. The financial and deal-related data are gathered from SDC Platinum and Bloomberg for targets and non-targets, respectively. Additionally, the macroeconomic factors were retrieved from FRED. In total, the resulting dataset contains observations satisfying the information- and deal-specific constraints from the hypothesis outlined in Chapter 3.2. Subsequently, the data are screened and filtered for extremities and anomalies (i.e. outliers and non-normal events).

Descriptive statistics of the pooled sample's independent variables are presented in Appendix A. Following is an analysis of the distribution of observations in the target- and non-target sample.

Figure 1 displays the takeover activity in the US tech-industry during the period of 1993 - 2018, and the overall trend is in line with takeover-theory on global merger waves and major global events. However, the sample shows no clear indication of the *fifth merger wave* (1993 - 2000) until the run-up of the *dot.com-bubble*, but shows a clear indication of the *sixth merger wave* (2003 - late 2007). Additionally, the sample is in line with the regulatory and legislative matters concerning US investors through 2012 - early 2013, that was ultimately dealt with by the FED, who maintained an accommodative monetary policy to raise investors' confidence in late 2013, leading back to the surge of deals in early 2014.

A possible explanation for the sample's reduction in acquisitions in 2017 - 2018 could be related to the economic growth in the US following the election of Donald Trump as President in November 2016, driving the Nasdaq Composite up by 44% over the following two years (Nasdaq, 2019), possibly driving valuations past what acquirers were willing to put on the table for targets. An additional explanation could be that all the 2017-2018 deals were not necessarily completed at the time of the data collection.

Figure 1 - Estimation and hold-out period, target sample
The count of takeovers during the whole sample period, gathered from the SDC Platinum.

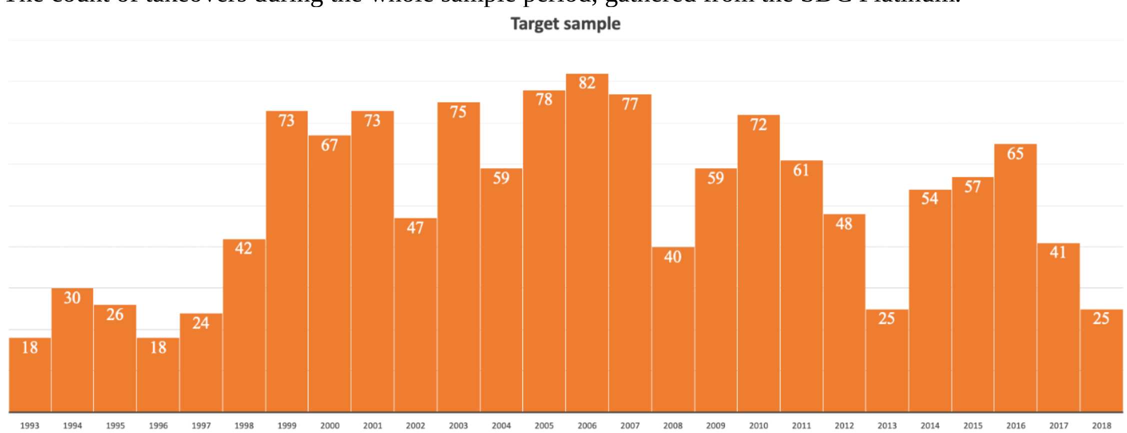
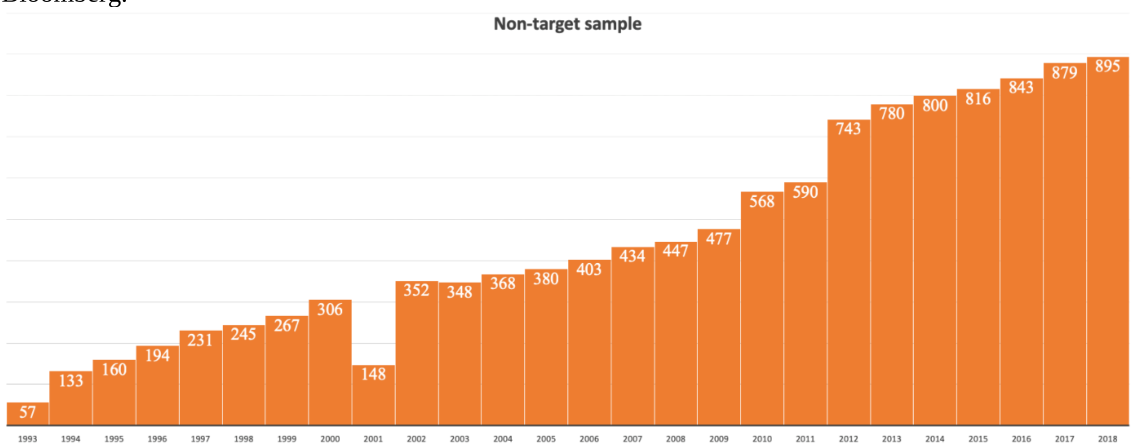


Figure 2 displays the non-target sample (control group) in the period 1993 - 2018, which shows consistent growth in the number of listed US tech companies, and the data are consistent with reports on how many tech-firms survived the dot.com bubble, approx. 48% (Dotcomarchive, 2004). However, the increase of listed firms in 2002 could to a large extent be explained by re-listings after Chapter 11[13] reorganizations.

Furthermore, the relative growth in the tech-industry could explain why the aggregate number of listed firms does not decrease due to a relative decrease in IPOs offsetting acquisitions during (peaks of) merger waves. In addition, the substantial growth in aggregate numbers in 2010 and 2012 could to some extent be explained by reorganizations of tickers and the listings of foreign companies, more specifically Chinese, on US exchanges.

Figure 2 - Estimation and hold-out period, non-target sample
The count of non-targets in the tech-industry during the whole sample period, gathered from Bloomberg.



4.3 Investment strategies

The hold-out sample is an extension of the pooled target/non-target sample data for the period 2015 – 2018, and is used to test the predictive power and successfulness of the model. Furthermore, the prices of the Nasdaq Composite index are gathered as a proxy for market returns in the tech-industry in order to calculate the excess returns of the investment portfolios in Chapter 6.3.

[13] Chapter 11 is a complex form of bankruptcy that involves a reorganization of a debtor's business affairs, debts and assets. Corporations generally file Chapter 11 if they require time to restructure their debts. This version of bankruptcy gives the debtor a fresh start.

5. Methodology

5.1 Announcement returns

As proposed by MacKinlay (1997), the standard event study methodology is applied when calculating the CAAR for target shareholders around deal announcement, in order to test the null-hypothesis[14]. The recommended approach has its foundation from the market model for calculating abnormal returns, which assumes the return of a given security is related to the return of the market portfolio, and is calculated as,

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

where α and β are the market model parameters, R_i is the expected return on a given security *i* at day *t* and R_m *is* the return on the market portfolio at day *t*.

The abnormal return is calculated as the difference between the realized return and the expected return previously outlined. Formally, the abnormal return is calculated as,

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

where *AR* is the abnormal return for firm *i* at day *t* in the event period and *R* is the realized return for firm *i* at day *t* in the event period. By adding up the *AR's* for each firm in the event window, *CARs* are calculated:

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

where *CAR*(t_1, t_2) is the *CAR* for firm *i* between the starting date (t_1) and the ending

[14] H0: No significant positive CAR from t days prior to t days post announcement date

date *(t_2)* of the event window. Finally, the *CAAR* is calculated as the average *CAR* for all 726 target firms within the event window.

The estimation window of trading days used to calculate the estimated beta should be unaffected by the takeover. However, evidence on the appropriate number of trading days is inconclusive. Some researchers find evidence for there to be a significant run-up in the period prior to takeover announcement. Brown and Warner (1985) suggested using 239 trading days while Goergen and Renneboog (2004) proposed 195, due to this run-up in the target price. Other studies find no evidence of a significant run-up in the two-month period prior to the announcement (Schwert, 1996; Eckbo, 2009), and hence use an estimation period of 50 trading days. This study uses an estimation period of 120 trading days.

5.2 Predicting takeover targets

As mentioned, this study seeks to distinguish targets from non-targets in the US tech-industry on the basis of public information, and to form an investment portfolio based on the results to test whether there are abnormal returns to be gained from such a strategy. In accordance with Palepu (1986), the study applies the logistic regression model due to the binary nature of the outcome from the model. That is, since firms will either be classified as targets or non-targets, the outcome of the model is binary, and thus it is appropriate to apply the logistic regression model. Hence, the explanatory variables are regressed on a target dummy variable in order to determine the impact of firm-specific, industry-specific and macroeconomic factors on the takeover likelihood.

The target dummy (*Y*), i.e. the dependent variable in this regression, is regressed on several explanatory variables. The conditional probability $P(Y = 1 \mid X = x)$ that *Y* equals one (from now on referred to as $p(x)$) is conceptually different from a linear function because it must be between zero and one. A logit regression model combines the selected variables to estimate a prediction model and returns the probability to a value between one and zero. This would not be possible with a simple linear regression model (Agresti & Finlay, 2009). Agresti & Finlay (2009) therefore suggest using the logistic transformation $log(p/1-p)$, which gives the logistic regression model:

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

where *x* are independent variables. By solving equation (5.4) for *p(x)*, the takeover probability can be expressed in the following manner,

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

Hereby, maximum likelihood estimation is used to fit the model as this achieves more precise results than with the OLS method (Agresti & Finlay, 2009).

Lastly, to consider the time-varying aspect of the *x*-variables and to find the functional relationship between the independent variables and the acquisition likelihood in a given period, the following equation is applied,

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

where *p(i,t)* describes the takeover probability of firm *i* at time *t*, *x(i,t)* is a vector of the independent firm-specific, industry-specific and macroeconomic variables, and lastly β is a vector of parameters that have to be estimated.

5.3 Investment strategies

To investigate the practical effectiveness of this takeover prediction model, two separate investment strategies will be utilized to create portfolios. The portfolios will be rebalanced on an annual basis to account for changes in takeover probabilities. Transaction costs will not be considered, as these are assumed to be small given the annual rebalancing. Furthermore, the effectiveness of the strategies will be measured against the returns of the Nasdaq Composite.

By considering the estimated takeover probability from the model against a predefined cut-off probability, the model distinguishes between the firms in the data as either targets or non-targets. Whenever the probability exceeds the cut-off probability, the observation will be classified as a target. The two investment strategies utilized in this study differ in the way they calculate the cut-off probability, which is explained in further detail below.

5.3.1 Minimum misclassification

The first investment strategy utilized in this study replicated the strategy proposed by Palepu (1986). Palepu's study assumed that the cost of wrongly classifying a target as a non-target is equal to the cost of including the target in the investment portfolio. The study therefore presented the objective of minimizing the number of misclassifications made by the model, as this is hypothesized to generate larger abnormal returns. Hence, based on Palepu (1986), the derivation of the minimal misclassification selection criterion is presented below,

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

where S is the current stock price of a firm, S_1 is the common perception of the stock price of the firm if it is acquired and S_2 if the firm is not acquired. Lastly, q is the takeover probability in the eyes of the market, i.e. the market's perception of the probability that the firm in question will actually be acquired.

Denoting $C_1 = S_1 - S$ as the payoff when the firm is actually acquired, and $C_2 = S_2 - S$ as the payoff when the firm is not acquired, ensures that the expected payoff, based on the market probability *q*, equals zero. Hence,

(5.8) $$qC_1 + (1-q)C_2 = 0$$

Now, the additional information is incorporated from the model, i.e. the estimated takeover probability *d* for firm *i*. Assuming that the view of the market on the values of S_1 and S_2 are shared, the expected payoff changes depending on the relationship between *q* and *d*. By applying Bayes' formula, the takeover probability (given p) can be described as;

(5.9) $$P(i = target \mid d) = \frac{qP_1\ (\ d \mid i{=}target)}{qP_1\ (\ d \mid i{=}target) + (1-q)P_2(d \mid i{=}non-target)}$$

where $P_1(d\ |target)$ is the conditional probability density of observing *d* if firm *i* proves to be a target and $P_2(d \mid non - target)$ is the conditional probability density of observing *d* if firm *i* is a non-target. Substituting $P_1(d\ |target)$ into equation (5.6), one can see that firm *i* can have an expected positive payoff if:

(5.10) $$P(target \mid d)C_1 + (1 - P(target \mid d))C_2 \geq 0$$

Furthermore, substituting equation (5.7) into (5.8), the equation can be rewritten as,

(5.11) $$\frac{P_1(d \mid target)}{P_2(d \mid non{-}target)} \geq \frac{-(1-q)C_2}{qC_1}$$

Hence, a firm with a predicted takeover probability *d*, that satisfies equation (5.9) will have an expected payoff larger than zero. If budget constraints are assumed to be an insignificant factor, one can maximize returns by identifying and investing in all firms that are classified as targets through this model.

Furthermore, considering the relationship presented in equation (5.6), the equation (5.9) can be re-written:

$$(5.12) \qquad \frac{P_1(d \mid target)}{P_2(d \mid non\text{-}target)} \geq 1$$

This condition indicates that classifying firms as targets and non-targets is the optimal selection criterion when the firm's marginal probability of observing *d* is larger than the marginal probability of observing *d* when the firm is a non-target, given that the firm is a target. Hence, the cut-off probability is observed at the intersection between the takeover likelihood distribution of actual targets and non-targets.

5.3.2 Maximum targets

As mentioned in Chapter 2.2.2, Powell (2001) argues that Palepu (1986) wrongfully assumes equality between the costs (loss of abnormal return) of Type I and Type II errors, which is unrealistic because the gains to target firms prior to takeover exceed those to firms that are not acquired. Hence, if the goal is to maximize abnormal returns from investing in predicted targets, then the optimal criterion for portfolio selection should be to maximize the number of actual targets in the portfolio rather than to minimize the proportion of misclassified non-targets.

Hence, the strategy used in Powell (2001) to try to generate abnormal returns by identifying takeover targets is to split the data into ten deciles based on the estimated takeover probability generated by the model and then calculate the C-ratio of targets within each decile. The lowest takeover probability within the decile with the highest C-ratio then becomes the threshold probability for classifying the observations in the hold-out sample as targets or non-targets. Thus, the second investment strategy of this study follows the ideas proposed by Powell (2001).

6. Findings

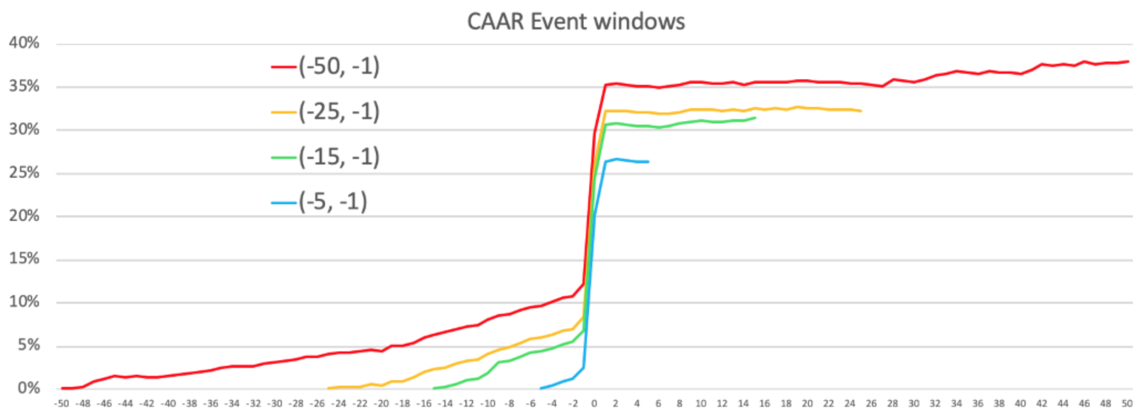
The empirical results are presented in three parts. Chapter 6.1 examines takeover returns across multiple event windows in the US tech-industry during the period 1993 - 2018. Chapter 6.2 develops and examines the takeover prediction model and the characteristics of takeovers. Finally, Chapter 6.3 tests the model's ability to form a successful investment strategy on the hold-out sample during the period 2015-2018.

6.1 Takeover announcement returns

The empirical results reveal that target shareholders in the US tech-industry experience significant returns during takeover announcements, in line with the findings of Kohers & Kohers (2000). The event windows [-5, +5], [-15, +15], [-25, +25] and [-50, +50] observe CAARs of 26.12%, 31.14%, 32.18% and 37.62%, respectively, as exhibited in Figure 3.

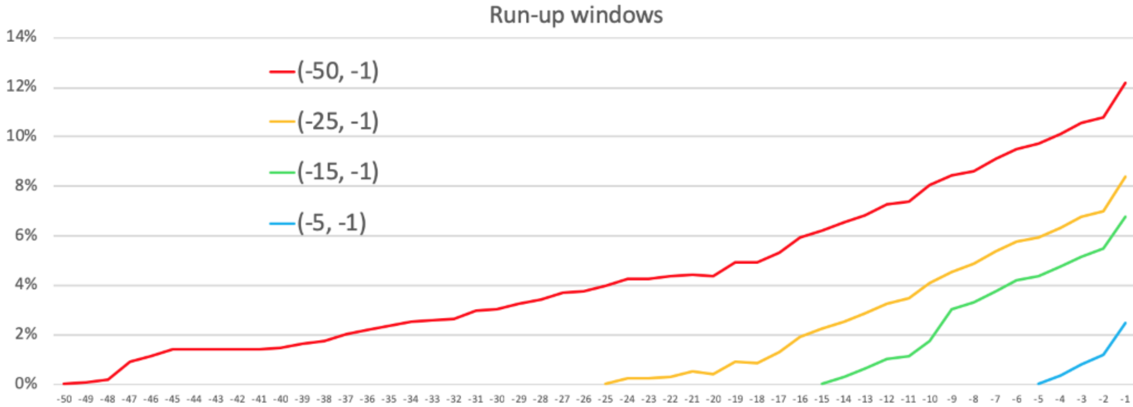
Figure 3 - CAAR, all event windows

CAAR to target shareholders for the entire sample over varying long and short event windows.



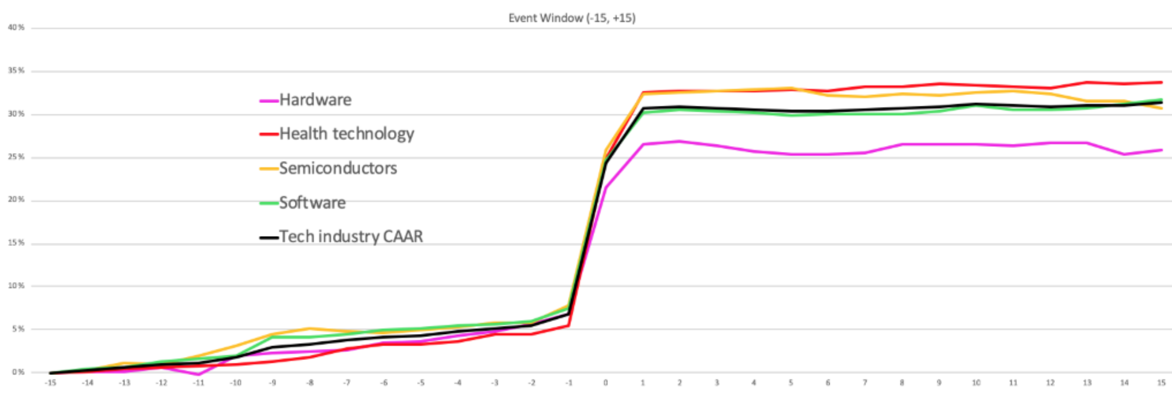
Evidence also suggests that run-up returns in the windows [-5, -1], [-15, -1], [-25, -1] and [-50, -1] range between 2.51% and 12.18%. However, run-up returns are not observable more than two months (approx. 48 trading days) prior to announcement, and the run-up in the window [-50, -1] indicates significant levels of possible information leakage, rumors and insider trading prior to announcement, in line with Schwert (1996) and Eckbo (2009).

Figure 4 - CAAR, run-up event windows
CAAR to target shareholders for the entire sample over varying event windows displaying the average run-up return.



When decomposing the event window [-15, +15] into sub-sectors, there appears to be indications of minor differences in returns between sectors, as *hardware* (purple line in Figure 5, below) can be seen lagging slightly behind the rest of the industry, which could be explained by the hardware-sector being relatively less affected by disruptive changes than the rest of the industry. However, in total the sub-sectors appear coherent in behavior. Additionally, there are no signs of overshooting and later corrections of share prices, indicating insignificant levels of noise in the sample.

Figure 5 - CAAR, sub-industries
CAAR to target shareholders for the entire sample over four main sub-industries.



These results lead to the rejection of the null hypothesis, in favor of the alternative hypothesis to conclude that target shareholders in the US tech-industry do receive significant positive CAARs during takeover announcements.

This supports the takeover prediction model's underlying assumption that target shareholders gain abnormal returns, implying that an accurate takeover prediction model should be able to generate abnormal returns if the market efficiency hypothesis fails.

6.2 Takeover prediction model

On the basis of the results in Chapter 6.1, and the ten hypotheses formulated in Chapter 3.2, five prediction models are developed. The first model effectively replicates the model proposed by Palepu (1986) on the US tech-industry, which includes the firm-specific hypothesis (inefficient management, firm size, growth-resource mismatch and undervaluation) and Gort's (1969) theory of economic disturbance. The second model extends on Palepu's initial model by adding Brar et al. (2009) hypotheses of leverage and liquidity, as well as revenue growth as an additional explanatory variable for inefficient management. The third model includes the hypothesis of macroeconomics, both behavioral and neoclassical, while the fourth model includes the industry-specific hypothesis on R&D expenditures by tech-firms. The fifth and final model is developed on the basis of removing hypotheses and variables of questionable economic logic and/or statistical insignificance, to only include the ones relevant specifically for the US tech-industry. The results are presented below in Table 4.

Due to high correlation between the three macro-related variables (*Fed Rate*, *Unemployment Rate* and *GDP*), only *Fed Rate* is included in the regressions to avoid a multicollinearity problem in the results, see Table D1.1 and D1.2 in Appendix D). The widely used multicollinearity-diagnostic Variance Inflation Factors (VIF) is applied to account for the issues and suggests removing the *Unemployment rate*- and *GDP*-factor.

Table 4 - Fixed effects logit regressions

Summary of the results from five logit regression models, starting with a replication of Palepu (1986) and ending with the model found to be the best fit for tech-companies in the US.

		Estimates				
Variables	Exp. sign	Model I (Palepu)	Model II (Brar et al.)	Model III (Macro)	Model IV (Industry-specific)	Model V (Prediction)
ROE	(-)	0.00 (0.40)	0.00 (0.64)			
Net book assets	(-)	-0.00*** (-3.20)	-0.00*** (-4.55)	-0.00*** (-5.71)	-0.00*** (-4.89)	-0.00*** (-5.59)
GRMM dummy	(+)	-0.11 (-0.92)	-0.11 (-0.80)			
IndDist	(+)	0.06 (0.61)	0.09 (0.95)	0.20** (1.98)	0.19* (1.80)	0.24** (2.29)
Market/Book	(-)	0.00 (0.14)				
Price/Earnings	(-)	-0.00 (-0.25)	-0.00 (-1.19)			
Revenue growth 2Y	(-)		-059*** (-6.12)	-0.84*** (-7.23)	-0.76*** (-6.50)	-0.83*** (-683)
ln(Revenue)	(-)			0.19*** (7.06)	0.12*** (4.34)	0.18*** (663)
Debt/Assets	(+)				-0.42** (-2.08)	-0.46** (-2.23)
Debt / Equity	(+)		0.00 (0.20)	-0.00 (-0.32)		
Profit margin	(-)		0.00** (2.31)	000 (0.22)		
Div. Yield	(-)		0.96*** (6,86)	0.96*** (6.57)	093*** (6.27)	0.95*** (6.51)
Current ratio	(-)		-0.04*** (-3.24)	-0.03* (-1.89)	-0.03** (-2.23)	-0.04** (-2.74)
Fed Rate	(-)			016*** (4.13)	0.15*** (3.56)	0.16*** (3.96)
Nasdaq dummy	(+)			0.14 (1.21)	0.13 (1.12)	0.15 (1.25)
Price/Research	(-)				0.00*** (4.98)	0,00*** (4.83)
R&D growth	(+)				-0.16 (-1.37)	-0.17 (-1.38)
P/IAE	(-)				-0.00 (-0.76)	
R&D intensity	(+)				-0.00 (-0.04)	
Observations		2711	2711	2711	2711	2711
Likelihood ratio (Chi^2)		21.24	243.63	328.07	394.70	353.54
Probability > Chi^2		0.00	0.00	0.00	0.00	0.00
Pseudo R^2		0.01	0.13	0.18	0.21	0.22

The results in Table 4 show that there are multiple variables affecting the takeover likelihood of firms in the US tech-industry, and that the models extending on Palepu's (1986) base model (Model I) have a reasonably high measure of fit[15].

The results indicate evidence for the inefficient management hypothesis across models, with *2-year revenue growth* being significant at the 1-percent level in models II-V, after being included by Brar et al. (2009) as an additional variable to explain the hypothesis. The negative coefficient provides evidence for the hypothesis that inefficient management (and low growth) increases the takeover likelihood of firms in the US tech-industry. However, contrary to most prior studies, *ROE* is insignificant in models I and II, and is therefore excluded. Furthermore, *profit margin (PM)* is significant at the 5-percent level for Model II, but with an insignificant coefficient for models II and III, and is therefore excluded.

The results indicate evidence that firm size has an effect on takeover likelihood, with *Net Book Assets (NBA)* and the *natural logarithm of revenue (lnRev)* being significant at the 1-percent level for models I-V and models III-V, respectively. The coefficient for *NBA* however is close to zero, and the coefficient sign for *lnRev* is positive, opposite of what was expected (-), indicating that larger firms are more likely targets. This is contrary to the initial hypothesis that smaller firms are more likely targets, but could be explained by the fact that a lot of firms in the tech-industry are valued on the basis of expected future growth (McKinsey, 2016)**,** and hence, a firm might be more attractive as a potential takeover target if it is able to generate a reliable source of revenue in addition to having promising growth prospects.

[15] The goodness of fit-term, and the explanatory power of the model, is explained by the relationship between the estimated and observed value of the dependent variables and the chi-square value is used to test the relationship between the two, and not by the conventional R-squared as it is impossible for logistic regression using Maximum-Likelihood (ML) estimation instead of Ordinary Least Squares (OLS).

The *Growth-Resource Mismatch (GRMM)-dummy* is both insignificant and holds the opposite expected sign (-) in Model I and II, and is therefore removed. Furthermore, the results indicate no evidence for the popular undervaluation-hypothesis that *P/E* and *M/B* is an explanatory variable for takeover likelihood, as both are insignificant and with a zero-coefficient. Hence, the results indicate that firms valued at lower multiples are not more likely to be targets for acquisitions, contrary to the findings of Rhodes-Kropf, Robinson & Viswanathan (2005). However, *Dividend yield* as a measure of undervaluation is highly significant at the 1-percent level in models II-V which conflicts with the insignificant findings of *P/E* and *M/B.* This indicates that *Dividend Yield* might serve the model better if classified differently, for example under the firm size hypothesis, as dividends are usually only an option when a firm reaches an "optimal" size where further growth is impossible or undesirable (Redding, 1997).

The leverage hypothesis has a zero-coefficient and is statistically insignificant when testing for *D/E* in Model II and III. However, when substituting *D/E* for *(D/A)*[16] in Model IV and V, it is found to be significant but with the opposite expected sign (-). A negative coefficient is contradictory to the leverage hypothesis which assumes that financially distressed companies with high levels of debt are likely to be acquired, indicating that smaller levels of debt increase takeover likelihood. Furthermore, models II-V shows evidence of liquidity having explanatory power of takeover likelihood, as *Current Ratio* is significant to different degrees for all models. The negative sign indicates that firms with less capital to meet short-term financial obligations are more likely to be takeover targets. This result is intuitive, as firms lacking capital to repay debt are more likely to find themselves in a situation of financial distress and hence more likely to become a takeover target for acquirers looking to invest in discounted asset values.

[16] Debt-to-Assets

The evidence of the impact macroeconomic variables has on takeover probability in the US tech-industry is accounted for in models III-V by the Fed rate-variable. The results are somewhat ambiguous as the Fed rate is significant at the 1-percent level, but with the opposite expected sign (+). This could be explained by the fact that an increasing interest rate is a sign of a healthy economy, contrary to the popular assumption that acquisitions are more likely when funding is cheap, i.e. when the borrowing rate is low. This indicates that acquirers seek targets when the economy is prospering rather than stagnating.

The market sentiment-variable *NasdaqDummy* is insignificant, indicating no evidence of irrational investor behavior. Furthermore, the industry-specific hypothesis of economic disturbance is insignificant in Model I and II, but proven significant for models III-V between 5 to 10-percent levels, indicating that there is an effect on takeover likelihood if there have been acquisitions in the same sub-sector within 12 months prior to the takeover. There is however no evidence of the industry-specific hypotheses in regards to R&D-expenditures being a key driver for acquisitions in the US tech-industry, as *R&D-intensity* and *R&D-growth* are insignificant, and the *PriceResearch-ratio* is significant, but with a zero-coefficient.

In the following chapter, we apply the estimates from the fifth model in an attempt to test the model's ability to generate abnormal returns by investing in predicted targets. The fifth and final model is based on the 11 most influential and logical variables from models I-IV, indicating that variables from all hypotheses except the Growth-Resource Mismatch hypothesis are the most relevant for predicting takeover targets, explaining 22% of the variation in the dependent variable.

6.3 Prediction and investing

In the following chapter, the predictive power of the model is discussed and followed by a review of the performances of two portfolios which apply two different investment strategies on the basis of the predictions made by the model.

6.3.1 Predictive power

Model V provides the estimated coefficients needed to calculate takeover probabilities for the hold-out sample. The model predicts an average takeover probability of 23.55% for actual targets and 12.38% for actual non-targets in the estimation-sample. This indicates that the prediction model is able to separate the characteristics of a typical takeover target from those of non-targets to some degree in the US tech-industry.

The predicted takeover probabilities are further split into deciles to provide further insight into the predictive power of the model, presented in Table 5 below. Table 5 summarizes the probabilities and number of observations in the different deciles of the estimation sample, where 100% indicates the highest probability in the highest decile, and 10% indicates the highest probability in the lowest decile. The table indicates that target observations skews towards higher predicted probabilities than the non-targets, further indicating that the model provides some predictive power.

Table 5 - Takeover probability deciles, estimation sample

Overview of deciles indicating the highest probability within each decile, as well as the number of targets and non-targets within deciles, where 10% indicates the decile with the lowest probability and 100% the decile with the highest.

		10 %	20 %	30 %	40 %	50 %	60 %	70 %	80 %	90 %	100 %	Total
Targets	Probabilities	15.32%	18.62%	21.2%	22.93%	25.04%	28,00 %	31.16%	40.33%	76.37%	100.00%	21.43%
	Count	59	59	57	59	58	57	58	58	58	58	581
Non-targets	Probabilities	1.62%	8.72%	13.42%	16.42%	18.75%	20.9%	23.3%	26.21%	30.07%	97.34%	78.57%
	Count	215	212	213	213	213	214	212	213	214	211	2130

6.3.2 Cut-off probabilities and portfolio returns

As outlined in Chapter 5.3, two investment portfolios are formulated, differing from each other due to contrasting ways of determining the cut-off probability to classify which observations are predicted targets or non-targets. All firms are classified as the former or the latter, and all firms classified as targets will be included in the investment portfolio.

6.3.2.1 Minimum Misclassification

Firstly, the investment strategy proposed by Palepu (1986) and described in Chapter 5.3.1 is utilized. Palepu (1986) suggests that the intersection between the probability density functions of the targets and non-targets in the estimation sample should constitute the cut-off probability in order to minimize the number of misclassifications made by the model. The intersection of the probability density functions in this study are displayed in Figure 6, below.

Figure 6 - Probability density functions

Overlapping density functions for predicted probabilities for actual targets and non-targets. The blue line displays the predicted probability density functions for actual targets, and the orange line for actual non-targets.

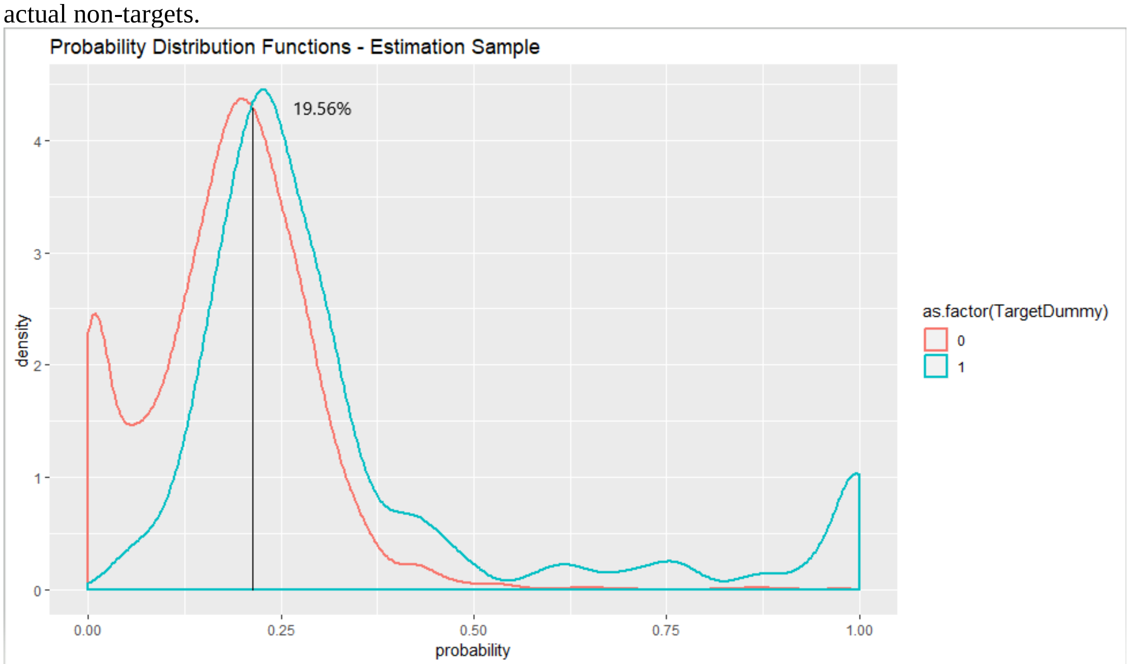


Figure 6 shows that there is a distinct difference between probabilities assigned the targets and non-targets, displaying that the average probability for actual targets are higher than that off non-targets, as previously mentioned. The probability threshold of 19.56% is further used to classify observations as targets or non-targets, along the lines of the *minimum misclassification*-approach.

Using a cut-off probability of 19.56%, the first portfolio of this study is formed, holding a total of 138 predicted targets for the period 2015 - 2018. As displayed in Table 6 below, the total actual number of targets in the same period is 145. However, the number of correctly predicted targets is substantially lower at only 38. In line with previous studies, forming a portfolio on the basis of the *minimum misclassification*-strategy proposed by Palepu (1986) results in a portfolio with large Type II errors (where non-targets are classified as targets). Furthermore, the resulting portfolio is unnecessarily enlarged by the number of misclassified targets, which in turn dilutes the effects of the correctly predicted targets in the portfolio. Somewhat surprisingly, the portfolio seems to indicate a large number of Type I-errors as well, where 107 actual targets are misclassified as non-targets.

Table 6 - Minimum misclassification portfolio composition

Overview of the predicted targets/non-targets using the cut-off probability from the *minimum misclassification*-strategy, the accuracy of the predictions and the returns of the portfolio formed, Portfolio I.

	Targets				Non-targets				Portfolio I		
Sample	Actual	Predicted	Correct	Type I error	Actual	Predicted	Correct	Type II error	Nasdaq Composite	Portfolio returns	Abnormal returns
2015	40	38	6	34	222	224	190	32	5.94%	1.96%	-3.98%
2016	54	50	15	39	224	228	189	35	9.8%	22.04%	12.24%
2017	28	39	9	19	206	195	176	30	27.16%	13.92%	-13.24%
2018	23	11	8	15	23	35	20	3	-5.3%	1.74%	7.04%
Total	**145**	**138**	**38**	**107**	**675**	**682**	**575**	**100**	**37.6%**	**39.66%**	**2.06%**

By investing in the *minimum misclassification*-portfolio on the first trading day of the year with annual portfolio rebalancing, i.e. for the predicted targets in 2015 one would invest on the first trading day of the year and hold for the whole year, the CAR generates a total of 2.06% excess return over the period 2015 - 2018.

6.3.2.2 Maximum targets

Furthermore, the investment strategy proposed by Powell (2001) and outlined in Chapter 5.3.2 is followed in the second investment portfolio. Powell argued that if the main objective of the estimated model is to predict takeover targets in order to maximize abnormal returns to the portfolio, the selection criterion to determine which companies are predicted to be targets or non-targets should be constructed in order to maximize the number of targets in the portfolio rather than minimizing the number of misclassifications. Hence, the estimated takeover probabilities of the model are split into ten decile portfolios, and the portfolio with the highest concentration of targets determines the threshold, i.e. the lowest probability in the decile portfolio with the highest target concentration is set as the cut-off probability.

Table 7 - Maximum target concentration ratios and cut-off

Concentration ratios of targets within each decile in the estimation sample.

	Maximum target concentration ratios (C-ratios)				
Deciles	Firms	Targets	Non-targets	C-Ratio	Cut-off
10 %	272	2	270	0.74%	0,00 %
20 %	271	22	249	8.12%	3.65%
30 %	272	32	240	11.76%	11.2%
40 %	270	44	226	16.3%	15.16%
50 %	271	50	221	18.45%	17.89%
60 %	271	64	207	23.62%	20.19%
70 %	272	70	202	25.73%	22.43%
80 %	270	64	206	23.7%	24.78%
90 %	271	85	186	31.37%	27.98%
100 %	**272**	**148**	**124**	**54.41%**	**33.16%**
Total	2712	581	2130		

As seen in Table 7 above, the decile with the highest C-ratio of targets in the estimation sample, consisting of 54.41% targets, sets the probability threshold at 33.16%. In turn, the second investment portfolio is formed, consisting of a total of 18 predicted targets for the period 2015-2018. Compared to Portfolio I the number of Type I-errors has risen to 130 misclassifications, however the number of Type II-errors drops significantly to only 3 misclassifications, down from 100 (see Table 8). Furthermore, in spite of predicting 18 targets with an 83.33% accuracy, Portfolio II seems to underperform compared to Portfolio I, yielding a market-adjusted return of -5.32% over the entire period.

Table 8 - Maximum target portfolio composition

Overview of the predicted targets/non-targets using the cut-off probability from the *maximum target-strategy*, the accuracy of the predictions and the returns of the portfolio formed, Portfolio II.

	Targets				Non-targets				Portfolio II		
Sample	Actual	Predicted	Correct	Type I error	Actual	Predicted	Correct	Type II error	Nasdaq Composite	Portfolio returns	Abnormal returns
2015	40	1	1	39	222	261	222	0	5.94%	2.2%	-3.74%
2016	54	9	7	47	224	269	222	2	9.8%	9.12%	-0.68%
2017	28	5	5	23	206	229	206	0	27.16%	15.73%	-11.43%
2018	23	3	2	21	23	43	22	1	-5.3%	5.23%	10.53%
Total	**145**	**18**	**15**	**130**	**675**	**802**	**672**	**3**	**37.6%**	**32.28%**	**-5.32%**

7. Conclusion, Limitations and Future Extension

7.1 Conclusion

The principal purpose of this study was to apply the existing methodology of target prediction on the US tech-industry using well-known influence factors, as well as a set of new factors considered relevant for the tech-industry, to explore the validity of the EMH. The results indicate that target shareholders receive 31.14% CAAR in the [-15, 15] event window with no significant differences between the sub-sectors, which indicates that an accurate prediction model should be able to generate abnormal returns to investors given an inefficient market.

As seen in *Model V*, the results indicate that several of the firm-specific hypotheses provide explanatory power for distinguishing targets from non-targets. Along the lines of previous studies, poorly performing firms with liquidity problems are more likely to become takeover targets. On the other hand, the findings suggest that takeover likelihood is positively correlated with leverage and firm size, indicating that acquirers prefer to buy companies that have already proven an ability to grow, as opposed to buying at an earlier stage in the hopes of buying potential "gazelles" [17]. For the industry-specific hypotheses there are no indications of a significant relationship between R&D-expenditures, nor industry disturbances, and takeover probability. The macroeconomic factor *Fed rate* is significant in the model, although indicating that takeovers cluster when the borrowing rate is high, contrary to the popular assumption that M&A activity increases with cheaper funding. Another interpretation of the results is that takeovers cluster when the US economy is prospering rather than stagnating.

The estimated probabilities from the prediction model provides the basis for the two investment portfolios. Under the *minimum misclassification*-approach the probability threshold is set at 19.56%, resulting in the prediction of 145 targets in the period 2015-2018 and a prediction accuracy of 26.2%, which is substantially lower than the 83.3% accuracy of the portfolio from the *maximum target*-approach. The resulting CARs contradict the superior accuracy of the latter model, as the portfolio from the *minimum misclassification*-approach yields a market-adjusted return of 2.06%, compared to –5.32% from the *maximum target*-portfolio. As the models assume zero transaction costs and are not significantly different from zero, the results indicate that the market efficiency hypothesis holds and thus concludes that investing solely on the basis of a prediction model in the US tech-industry is not a viable investment strategy.

7.2 Limitations & Drawbacks

Concerning the limitations of the study, there are a few to keep in mind. Firstly, that it is infeasible to expect that a one-size-fits-all model will explain takeover activity, as there is varying rational and irrational behavior to account for.

Secondly, as the prediction model is based on the idea of market control, i.e. that acquisitions represent a disciplinary action for underperforming management, the model might miss takeovers with different motives.

[17] A company that has increased its revenues by at least 20% for four consecutive years or more

Thirdly, there are multiple limitations with regards to data. Primarily, the ratio between targets and non-targets can heavily affect the outcome of the results of the logit model and the cut-off probabilities. Secondarily, removing plausible outliers and extreme values eliminates large portions of the variance in the non-target observations. Consequently, by eliminating extreme values, the resulting model appeared to predict targets from non-targets with extreme accuracy and hence the extreme values of the non-targets remained in the data used in the prediction model.

Finally, the prediction model is partly built as a step-by-step integration of variables, a method Palepu (1986) argued would lead to "statistical overfitting", and hence not a clean method of building a general explanatory model to explain takeover probability.

7.3 Future Extension

The limitations from Chapter 7.2 should motivate further research on the topics highlighted in this study.

Firstly, it would be interesting for future research to further explore the ways in which a prediction model could be utilized, and to determine in which way it is optimal. A prediction model might not be very useful for investors seeking abnormal returns but could for example be useful for managers that are looking to expand through M&A and hence the model could be helpful for determining which candidates are the most attractive. As this study assumes takeovers happen as a disciplinary action, such an expansion would also take into account acquisitions with different motives.

Secondly, there are many ways of constructing investment portfolios on the basis of predicted takeover probabilities, only two of which are examined in this study. For example, forming a long-short portfolio that buys poorly performing high-probability firms and shorts the poorly performing low-probability firms is a logical way of constructing a more advanced portfolio, which could generate abnormal returns and thus possibly change the conclusion on market efficiency.

Thirdly, for future industry-specific studies on takeover prediction, a further expansion on which variables should be emphasized when predicting takeover targets in a single industry would be an important contribution to the existing body of knowledge. Capital Expenditure-variables could extend on, or replace, R&D-variables and adding an additional hypothesis on the effects of different ownership structures or corporate governance mechanisms would be a natural extension to the existing model. Furthermore, determining whether the logistic regression model is the optimal model for an industry-specific takeover prediction study has yet to be reviewed.

Lastly, applying the methodology used in this study on a tech-industry in other parts of the world (Europe, Asia etc.) could highlight useful similarities and differences explained by geographic separation and demographic differences in investor behavior.

Appendices

Appendix A – Data description and variable calculation

<u>Inefficient management hypothesis</u>

2-year revenue growth

Calculation: [Sales(t) / Sales(t-2))^(½)-1]

Database: SDC Platinum for targets, Bloomberg for non-targets

ROE

Calculation: Net income / Book value of equity

Database: SDC Platinum for targets, Bloomberg for non-targets

Profit margin

Calculation: Net income / Revenue

Database: SDC Platinum for targets, Bloomberg for non-targets

<u>Firm size hypothesis</u>

ln(Revenue)

Calculation: Revenue (in $m), ln(Revenue) calculated as the natural logarithm of revenues

Database: SDC Platinum for targets, Bloomberg for non-targets

Total assets

Database: SDC Platinum for targets, Bloomberg for non-targets

Elimination: Observations with missing values dropped.

Market capitalization (MCAP)

Calculation: Market capitalization (in $m) calculated as share price (t-1) x shares outstanding, where t is announcement date for targets and t is the last day of the year (31.12) for non-targets.

Database: SDC Platinum for targets, Bloomberg for non-targets

Net assets

Calculation: Total assets - Total liabilities

Database: SDC Platinum for targets, Bloomberg for non-targets

Leverage hypothesis

Debt / Equity

Calculation: Interest-bearing debt / Book value of equity

Database: SDC Platinum for targets, Bloomberg for non-targets

Debt / Assets

Calculation: Interest-bearing debt / Total assets

Database: SDC Platinum for targets, Bloomberg for non-targets

Elimination: Observations with missing values dropped.

Liquidity hypothesis

Current Ratio

Calculation: Current assets / Current liabilities

Database: SDC Platinum, Bloomberg and Compustat

Industry-specific hypothesis

R&D growth

Calculation: [R&D expense (t) / R&D expense (t-1)] -1

Database: Compustat

R&D intensity

Calculation: R&D expense / Revenue

Database: Compustat, SDC Platinum and Bloomberg

Price/Research Ratio

Calculation: MCAP / R&D expenditure

Database: Compustat, SDC Platinum and Bloomberg

Industry Disturbance Dummy

Calculation: Indicating (1) when there has been an acquisition in the same sub-sector during the last 12 months and (0) if not. Announcement date used for targets, year-end date used for non-target.

Database: SDC Platinum and Bloomberg

<u>Growth-Resource Mismatch hypothesis</u>

Growth-Resource Mismatch Dummy

Calculation: Indicating (1) if firm has:

1) Above average 2-year revenue growth,
below average liquidity ratio (current assets / current liabilities) and
above average Debt/Equity

or;

2) Below average 2-year revenue growth,
above average liquidity ratio and
above average Debt/Equity

Database: Compustat, SDC Platinum and Bloomberg

<u>Undervaluation hypothesis</u>

Market / Book

Calculation: MCAP / Book value of equity

Database: SDC Platinum, Bloomberg

Dividend yield

Calculation: Annual dividend per share / Share price

Database: Compustat

Price-Earnings

Calculation: MCAP / Net income

Database: SDC Platinum, Bloomberg

<u>Market sentiment hypothesis</u>

Nasdaq Dummy

Calculation: Indicating (1) if positive 12-month return on the Nasdaq Composite Index prior to announcement date (targets) / year-end date (non-targets).

Database: Yahoo Finance

<u>Macroeconomic factors</u>

Fed Rate

Calculation:

Database: Federal Reserve Economic Data

GDP growth (yearly)

Calculation: [GDP(t) / GDP(t-1)]

Database: Federal Reserve Economic Data

Appendix B - Descriptive statistics on data

Table B1 – Descriptive statistics for targets in the estimation sample

Overview of the variables and respective hypotheses included in Models I-V with descriptive statistics of the data specifically for the target observations in the estimation sample.

Hypotheses	Targets					
Variables	Count	Mean	Median	Std.Dev	Min. value	Max. value
Inefficient management						
2-year sales growth	581	9,56 %	4,85 %	19,68 %	-22,02 %	171,78 %
Return on equity	581	-4,19 %	5,30 %	506,45 %	-7137,75 %	6300,00 %
Profit margin	581	3,59	0,00	77,68	-172,50	1846,91
Firm size (in $M)						
Net book assets	581	619,77	104,40	3807,83	-83,10	83404,00
ln(Revenue)	581	5,17	5,00	2,13	-1,26	11,64
Growth-Resource Mismatch						
Dummy	581	0,81	1,00	0,39	0,00	1,00
Undervaluation						
Market/Book	581	0,11	2,34	95,96	-2273,28	215,67
Price/Earnings	581	-2,51	11,20	242,42	-3267,62	2230,20
Leverage						
Debt/Equity	581	1,20	0,55	7,10	-70,00	118,31
Debt/Assets	581	0,39	0,36	0,23	-0,17	1,15
Liquidity						
Current ratio	581	3,74	2,66	4,37	0,13	50,64
Dividend yield	581	3,52 %	0,00 %	40,44 %	0,00 %	709,99 %
Liquidity ratio	581	0,36	0,36	0,26	-0,77	0,98
Industry-specific						
Industry disturbance dumn	581	0,58	1,00	0,49	0,00	1,00
R&D-growth	581	8,02 %	0,00 %	47,14 %	-100,00 %	587,80 %
R&D-intensity	581	4,30	0,06	61,51	0,00	1410,21
Price/Research	581	396,17	7,64	2259,14	0,00	34377,36
Macroeconomic factors						
Fed rate	581	4,08 %	4,27 %	1,27 %	1,80 %	7,09 %
GDP growth	581	2,33 %	2,55 %	1,62 %	-2,68 %	4,90 %

Table B2 – Descriptive statistics for non-targets in the estimation sample

Overview of the variables and respective hypotheses included in Models I-V with descriptive statistics of the data specifically for the non-target observations in the estimation sample.

Hypotheses			Non-Targets			
Variables	Count	Mean	Median	Std.Dev	Min. value	Max. value
Inefficient management						
2-year sales growth	2130	771,00 %	17,87 %	23291,41 %	-100,00 %	1018560,00 %
Return on equity	2130	-32,50 %	2,33 %	2087,95 %	-79060,82 %	42671,43 %
Profit margin	2130	-4293,64	0,01	49791,32	-1323459,92	456980,00
Firm size (in $M)						
Net book assets	2130	1611,66	133,46	6580,94	-377,94	111547,01
ln(Revenue)	2130	4,21	4,79	4,86	-25,33	12,12
Growth-Resource Mismatch						
Dummy	2130	0,83	1,00	0,37	0,00	1,00
Undervaluation						
Market/Book	2130	-0,07	0,00	10,06	-405,92	225,61
Price/Earnings	2130	-0,25	0,00	15,57	-698,39	88,11
Leverage						
Debt/Equity	2130	1,83	0,43	106,61	-1771,88	4564,58
Debt/Assets	2130	0,48	0,33	1,60	0,01	44,52
Liquidity						
Current ratio	2130	4,67	3,18	5,79	0,01	136,10
Dividend yield	2130	0,05 %	0,00 %	0,24 %	-1,56 %	4,73 %
Liquidity ratio	2130	-5,62	0,39	205,48	-9373,19	2,58
Industry-specific						
Industry disturbance dumm	2130	0,57	1,00	0,50	0,00	1,00
R&D-growth	2130	18,47 %	7,86 %	72,67 %	-99,42 %	1326,44 %
R&D-intensity	2130	29637,78	0,17	345458,02	0,00	10967000,00
Price/Research	2130	30,51	14,86	73,40	0,05	2072,11
Macroeconomic factors						
Fed rate	2130	3,88 %	4,01 %	1,29 %	1,80 %	7,09 %
GDP growth	2130	2,22 %	2,55 %	1,76 %	-2,68 %	4,90 %

Table B3 – Descriptive statistics for targets in the hold-out sample

Overview of the variables and respective hypotheses included in Models I-V with descriptive statistics of the data specifically for the target observations in the hold-out sample.

Hypotheses			Targets			
Variables	**Count**	**Mean**	**Median**	**Std.Dev**	**Min. value**	**Max. value**
Inefficient management						
2-year sales growth	145	9,40 %	4,26 %	23,73 %	-26,28 %	166,58 %
Return on equity	145	-16,77 %	6,00 %	150,70 %	-1666,67 %	315,23 %
Profit margin	145	4,45	0,02	22,11	-13,21	152,96
Firm size (in $M)						
Net book assets	145	1175,40	313,70	3064,35	-10,20	24308,00
ln(Revenue)	145	4,76	5,08	1,87	-1,26	9,24
Growth-Resource Mismatch						
Dummy	145	0,69	1,00	0,46	0,00	1,00
Undervaluation						
Market/Book	145	3,54	1,36	17,40	-11,78	208,33
Price/Earnings	145	19,11	11,72	75,27	-328,13	676,16
Leverage						
Debt/Equity	145	2,48	0,72	16,30	-74,80	176,68
Debt/Assets	145	0,45	0,43	0,25	0,02	1,49
Liquidity						
Current ratio	145	3,23	2,22	4,09	0,35	45,62
Dividend yield	145	0,65 %	0,00 %	1,41 %	0,00 %	6,41 %
Liquidity ratio	145	0,31	0,29	0,25	-0,35	0,97
Industry-specific						
Industry disturbance dummy	145	0,61	1,00	0,49	0,00	1,00
R&D-growth	145	11,73 %	1,15 %	53,56 %	-53,03 %	584,96 %
R&D-intensity	145	6,82	0,15	36,08	0,00	339,19
Price/Research	145	33,02	0,76	216,60	0,00	1979,14
Macroeconomic factors						
Fed rate	145	2,19 %	2,14 %	0,37 %	1,84 %	2,91 %
GDP growth	145	2,20 %	2,00 %	0,41 %	1,88 %	3,00 %

Table B4 – Descriptive statistics for non-targets in the estimation sample

Overview of the variables and respective hypotheses included in Models I-V with descriptive statistics of the data specifically for the non-target observations in the hold-out sample.

Hypotheses	Non-Targets					
Variables	Count	Mean	Median	Std.Dev	Min. value	Max. value
Inefficient management						
2-year sales growth	675	126,27 %	4,18 %	1275,55 %	-100,00 %	22090,41 %
Return on equity	675	3,17 %	1,16 %	603,84 %	-5199,63 %	11811,44 %
Profit margin	675	-2995090,7	-0,05	18054367,99	-352860992	4,92
Firm size (in $M)						
Net book assets	675	2210,34	124,62	10112,56	-3408,00	134047,01
ln(Revenue)	675	2,17	4,64	9,05	-25,33	12,34
Growth-Resource Mismatch						
Dummy	675	0,79	1,00	0,41	0,00	1,00
Undervaluation						
Market/Book	675	0,01	0,00	0,17	-2,61	2,66
Price/Earnings	675	0,06	0,00	1,14	-14,76	14,53
Leverage						
Debt/Equity	675	0,14	0,50	15,83	-348,88	48,18
Debt/Assets	675	1,22	0,41	6,93	0,01	143,45
Liquidity						
Current ratio	675	4,23	2,79	4,66	0,00	55,26
Dividend yield	675	0,10 %	0,00 %	0,27 %	0,00 %	2,68 %
Liquidity ratio	675	-5,76	0,40	124,32	-3215,22	0,98
Industry-specific						
Industry disturbance dummy	675	66,52 %	100,00 %	47,19 %	0,00 %	100,00 %
R&D-growth	675	0,10	0,06	1,17	-24,30	15,15
R&D-intensity	675	19804,36	0,20	131864,61	0,00	2692510,08
Price/Research	675	25,44	15,00	44,90	0,08	745,93
Macroeconomic factors						
Fed rate	675	2,18 %	2,14 %	0,25 %	1,84 %	2,91 %
GDP growth	675	0,022148889	0,02	0,003296415	0,01875	0,03

Appendix C - Previous empirical studies

Table C1 - Overview of all hypotheses and variables in previous empirical studies

This table summarizes the various firm-specific hypotheses and variables used in empirical studies on takeover prediction. The "Expected sign" indicates whether an increase in the proposed variables will affect takeoverlikelihood of a firm positively or negatively.

Hypotheses	Variables	Expected sign	Study
Inefficient management	- Return on equity	Neg.	- Palepu (1986) - Brar, Giamouridis & Liodakis (2009)
	- Average excess return	Neg.	- Ambrose & Megginson (1992) - Palepu (1986)
	- Operating profit / Capital employed	Neg.	- Powell (2001;2004)
	- Tobin's Q	Neg.	- Cremers, Nair & John (2009) - Brar, Giamouridis & Liodakis (2009)
	- Profit margin & growth** - Profit / Capital - Asset turnover & growth - Market share - Return on sales - Return on capital - Sales growth*	Neg.	- Brar, Giamouridis & Liodakis (2009) - Palepu (1986)
	- Pre-tax profit / Sales - Pre-tax profit /Shareholders equity - Pre-tax profit growth last 3 years - Avg. Dividend last 3 years / Shareholders equity - Dividend growth last 3 years	Neg.	- Barnes (1999)
Firm size	- Net book assets	Neg.	- Palepu (1986) - Ambrose & Megginson (1992) - Powell (2001)

	- Market capitalization**	Neg.	- Barnes (1999) - Cremers, Nair & John (2009) - Brar, Giamouridis & Liodakis (2009)
	- Sales*** - No. Of employees	Neg.	- Brar, Giamouridis & Liodakis (2009)
Growth-resource mismatch	- Growth-resource dummy based on sales growth, liquidity and leverage	Pos.	- Palepu (1986)- Ambrose & Megginson (1992)- Powell (2001;2004)
Undervaluation	- Price / Earnings***	Neg.	- Dietrich & Sorensen (1984) - Ambrose & Megginson (1992) - Brar, Giamouridis & Liodakis (2009)
	- Market / Book	Neg.	- Palepu (1986) - Ambrose & Megginson (1992) - Powell (2001)
	- Market cap. / Shareholders equity		- Barnes (1999)
	- Dividend yield*** - Price /Book	Pos. / Neg.	- Brar, Giamouridis & Liodakis (2009)
Leverage	- Long term debt-to-assets		- Dietrich & Sorensen (1984) - Brar, Giamouridis & Liodakis (2009)
	- Total debt-to-assets		- Cremers, Nair & John (2009) - Brar, Giamouridis & Liodakis (2009)
	- Short term debt-to-assets - Total debt-to-equity	Pos.	- Brar, Giamouridis & Liodakis (2009)
Liquidity	- Cash-to-capital***	Neg.	- Brar, Giamouridis & Liodakis (2009)
Ownership structure	- No. of institutional managers following firms - Institutional shareholding (%) - Change in institutional shareholding* - Officer and director shareholding (%)		- Ambrose & Megginson (1992)

	- Dummy indicating existence of institutional blockholder		- Cremer, Nair & John (2009)
Momentum	- 3-month price momentum*** - 12-month price momentum - Avg. Trading volume-to-MCAP*** - Analyst earnings revisions	Pos. / Neg.	- Brar, Giamouridis & Liodakis (2009)
Age	- Age of firm since listed - Age dummies	Neg.	- Brar, Giamouridis & Liodakis (2009)
Barrier to entry	- Minimum efficient scale (MES) - Market share - Herfindahl index	Neg.	- Brar, Giamouridis & Liodakis (2009)
Rumors	- Annual number of articles speculating on takeover possibility	Neg.	- Brar, Giamouridis & Liodakis (2009)

Appendix D - Correlation Matrix

Table D1.1 – Correlation matrix, independent variables

Variables	Target Dummy	GDP	FedRate	Unemp	lnRev	RevGrowth2y	ROE	PM	PE	MB	CR	DE
TargetDummy	1	0,02	0,07	-0,05	0,10	-0,02	0,01	0,04	0,01	0,01	-0,07	0,02
GDP	0,02	1	0,32	-0,27	0,01	-0,02	-0,02	0,01	-0,03	0,02	0,03	0,00
FedRate	0,07	0,32	1	-0,38	0,11	-0,02	-0,01	0,07	-0,04	-0,02	0,05	-0,02
Unemp	-0,05	-0,27	-0,38	1	0,03	0,02	0,01	0,02	0,02	0,02	-0,03	0,01
lnRev	0,10	0,01	0,11	0,03	1	0,01	0,02	0,46	0,01	0,00	-0,21	0,01
RevGrowth2y	-0,02	-0,02	-0,02	0,02	0,01	1	0,00	0,00	0,00	0,00	0,00	0,01
ROE	0,01	-0,02	-0,01	0,01	0,02	0,00	1	0,00	0,00	-0,04	0,00	0,09
PM	0,04	0,01	0,07	0,02	0,46	0,00	0,00	1	0,00	0,00	-0,03	0,00
PE	0,01	-0,03	-0,04	0,02	0,01	0,00	0,00	0,00	1	0,01	0,00	0,00
MB	0,01	0,02	-0,02	0,02	0,00	0,00	-0,04	0,00	0,01	1	0,00	0,01
CR	-0,07	0,03	0,05	-0,03	-0,21	0,00	0,00	-0,03	0,00	0,00	1	0,00
DE	0,02	0,00	-0,02	0,01	0,01	0,01	0,09	0,00	0,00	0,01	0,00	1
PriceResearch	0,13	0,02	0,07	-0,04	0,06	0,00	0,00	0,01	0,06	0,01	0,00	0,00
RDg2	-0,02	0,00	-0,03	-0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,03	0,00
RDintensity	-0,04	-0,01	-0,07	-0,01	-0,44	0,00	0,00	-0,89	0,00	0,00	0,04	0,00
DivYield	0,07	-0,03	0,00	0,04	0,00	0,00	0,00	0,00	0,00	0,01	-0,02	-0,02
PIAE	0,01	-0,02	0,00	0,03	0,02	0,00	0,00	0,00	0,00	0,00	-0,03	-0,01
GRMM	-0,02	0,01	0,02	-0,02	-0,16	-0,03	0,03	-0,03	-0,01	-0,02	0,30	-0,08
IndDist	-0,01	-0,09	-0,20	0,11	-0,03	-0,02	0,02	-0,01	0,01	-0,02	-0,01	-0,02
NasdaqDummy	-0,02	0,01	-0,01	-0,21	-0,03	-0,03	0,02	-0,02	0,00	0,03	0,01	0,00
NBA	-0,05	0,01	-0,04	0,00	0,20	-0,01	0,01	0,02	0,09	0,00	-0,06	0,01
LiquidityRatio	0,02	0,01	0,01	-0,03	-0,01	0,00	0,00	0,00	0,00	0,00	0,01	0,00
DtA	-0,03	-0,01	-0,05	-0,02	-0,15	0,00	0,01	-0,01	0,00	0,00	-0,06	0,00
CTC	-0,04	-0,03	-0,03	0,02	-0,12	0,00	0,00	-0,01	0,00	0,00	0,14	0,00

Table D1.2 – Correlation matrix, independent variables

Variables	Price/ Research	RDg2	RDintensity	DivYield	PIAE	GRMM	IndDist	Nasdaq Dummy	NBA	Liquidity Ratio	DtA	CTC
TargetDummy	0,13	-0,02	-0,04	0,07	0,01	-0,02	-0,01	-0,02	-0,05	0,02	-0,03	-0,04
GDP	0,02	0,00	-0,01	-0,03	-0,02	0,01	-0,09	0,01	0,01	0,01	-0,01	-0,03
FedRate	0,07	-0,03	-0,07	0,00	0,00	0,02	-0,20	-0,01	-0,04	0,01	-0,05	-0,03
Unemp	-0,04	-0,01	-0,01	0,04	0,03	-0,02	0,11	-0,21	0,00	-0,03	-0,02	0,02
lnRev	0,06	0,00	-0,44	0,00	0,02	-0,16	-0,03	-0,03	0,20	-0,01	-0,15	-0,12
RevGrowth2y	0,00	0,00	0,00	0,00	0,00	-0,03	-0,02	-0,03	-0,01	0,00	0,00	0,00
ROE	0,00	0,00	0,00	0,00	0,00	0,03	0,02	0,02	0,01	0,00	0,01	0,00
PM	0,01	0,00	-0,89	0,00	0,00	-0,03	-0,01	-0,02	0,02	0,00	-0,01	-0,01
PE	0,06	0,00	0,00	0,00	0,00	-0,01	0,01	0,00	0,09	0,00	0,00	0,00
MB	0,01	0,00	0,00	0,01	0,00	-0,02	-0,02	0,03	0,00	0,00	0,00	0,00
CR	0,00	0,03	0,04	-0,02	-0,03	0,30	-0,01	0,01	-0,06	0,01	-0,06	0,14
DE	0,00	0,00	0,00	-0,02	-0,01	-0,08	-0,02	0,00	0,01	0,00	0,00	0,00
PriceResearch	1	0,00	-0,01	0,00	0,00	0,04	0,00	0,01	-0,01	0,00	0,00	-0,01
RDg2	0,00	1	0,00	0,00	0,00	-0,02	0,00	0,00	0,00	0,00	0,00	0,00
RDintensity	-0,01	0,00	1	0,00	0,00	0,02	0,02	0,02	-0,02	0,00	0,00	0,01
DivYield	0,00	0,00	0,00	1	0,00	-0,01	0,01	-0,01	0,01	0,00	0,00	0,00
PIAE	0,00	0,00	0,00	0,00	1	-0,01	0,01	-0,02	0,01	0,00	0,00	0,00
GRMM	0,04	-0,02	0,02	-0,01	-0,01	1	0,01	-0,01	-0,07	0,03	0,04	0,02
IndDist	0,00	0,00	0,02	0,01	0,01	0,01	1	-0,03	0,04	-0,02	0,02	0,02
NasdaqDummy	0,01	0,00	0,02	-0,01	-0,02	-0,01	-0,03	1	-0,03	-0,01	-0,02	-0,01
NBA	-0,01	0,00	-0,02	0,01	0,01	-0,07	0,04	-0,03	1	0,00	-0,01	-0,02
LiquidityRatio	0,00	0,00	0,00	0,00	0,00	0,03	-0,02	-0,01	0,00	1	0,00	0,00
DtA	0,00	0,00	0,00	0,00	0,00	0,04	0,02	-0,02	-0,01	0,00	1	0,00
CTC	-0,01	0,00	0,01	0,00	0,00	0,02	0,02	-0,01	-0,02	0,00	0,00	1

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