Predicting Takeover Targets

An Empirical Analysis of the European Market

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Abstract

This thesis studies the influence factors for takeover prediction and the potential to generate abnormal returns based on takeover probabilities in the European market. A takeover prediction model is developed using conditional logit regression and a sample of 856 target and 18,808 non-target observations from 1996 to 2010. Studying the sixth merger wave and the differences between the markets of the United Kingdom (UK) and Continental Europe (CE) is new to this research area. The empirical analysis finds significant negative influences of sales growth, EBITDA-margin, current ratio and industry disturbances as well as positive relations of P/E-ratio and UK-firms on takeover probability. An out-of-sample test for 2011 and 2012 finds a predictive accuracy of 75.5% for the model, identifying 54% of targets and 76% of non-targets correctly. The derived yearly-rebalanced long-only investment strategy for the high takeover probability decile generates market-adjusted returns of 9.7% p.a. for the European market sample over the last 17 years. The results show large differences for both, this strategy and for takeover announcement returns between UK and CE targets.

Key words: Takeover prediction; Conditional logit; Abnormal return; Investment strategy
JEL classification: G34, G11, G14

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List of abbreviations

AR	abnormal return
CAR	Cumulative abnormal return
CAAR	Cumulative average abnormal return
CAGR	Compound annual growth rate
CAPEX	Capital Expenditures
CE	Continental Europe
EBITDA	Earnings before interest, taxes, depreciation and amortization
EQV	Equity value
GDP	Gross domestic product
GR	Growth-resource (dummy variable)
LR	Likelihood ratio
L3Y	Last three years
M&A	Mergers & acquisitions
M/B	Market to book
MSCI	Morgan Stanley Capital International (MSCI Inc.)
OLS	Ordinary least squares
P/E	Price to earnings
Q	Tobin's Q
ROE	Return on equity
SEC	Securities and Exchange Commission (United States)
SIC	Standard industry classification
S&P	Standard & Poor's
UK	United Kingdom
US	United States
$[-X_1, +X_2]$	Event window with a length of X_1 trading days before and X_2 after announcement

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1. Introduction

"Prediction is very difficult, especially about the future."

Nils Bohr, Nobel laureate in Physics

1.1 Motivation, research objectives and limitations

Corporate takeovers are widely researched events in financial markets. For a long time, the degree of takeover activity was negligible in Europe as compared to the market in the United States (US). However, over the last decades, the European M&A market continuously grew, first mainly in the United Kingdom (UK) and then all over the European continent. Especially the introduction of the Euro as a common currency at the end of the 1990s triggered intra-European cross-border M&A due to rising competitive pressure (Martynova & Renneboog, 2006, pp. 2-3). Therefore, the fifth and sixth merger wave were largely shaped by the European takeover market, which is still dominated by the UK.

It is well known from empirical research that target shareholders receive large returns in the process of a takeover bid (see, e.g. Andrade, Mitchel & Stafford, 2001). Hence, finding ways to identify these companies before a takeover bid takes place remains one of the unaccomplished visions for many people in the financial industry. Various studies have suggested models for takeover prediction based on publicly available information for predominantly the US and UK markets (see, e.g. Palepu, 1986; Ambrose & Megginson, 1992; Barnes, 1990/1999; Cudd & Duggal, 2000; Powell, 1997/2001/2004; Brar, Giamouridis & Liodakis, 2009). While some have the sole purpose of identifying new influence factors for takeover activity or takeover motives, others are driven by the desire to generate abnormal returns.

The goal of this thesis is to identify influence factors and to test the feasibility of takeover prediction in the European market. Furthermore, the potential to generate abnormal returns through takeover probability-driven investment strategies is examined. Based on the hypotheses in the context of the market for corporate control, suggested by Palepu (1986), a prediction model is developed, adding three additional hypotheses for leverage, liquidity and investment behavior. The prediction model is estimated using a sample of 856 targets and 18,808 non-targets for the 15-year period from 1996 to 2010. In addition, the prediction model is applied to observations from 2011 and 2012 in an out-of-sample test.

This thesis contributes to the existing literature in three main points. First, the analysis of observations from 1996 to 2012 not only covers the fifth, but also the sixth merger wave. Therefore, the developments in the European M&A market over the last decade can be integrated, which previous studies did not address (see, e.g. Powell, 2004; Brar, Giamouridis & Liodakis, 2009). Second, a conditional logit regression model, matching observation year and industry is employed to improve the prediction capability of the model. Third, the widespread assumption of differences between the takeover

market in the UK and Continental Europe is examined with regard to target announcement returns and the potential to generate returns through a portfolio of high takeover probability firms.

Clearly, the various rational and irrational motives for takeovers make a one-size-fits-all model for the explanation of all takeovers unfeasible. Hence, the prediction model is based on the ideas of the market for corporate control, which suggests that takeovers are a disciplinary procedure for underperforming management (see, e.g. Jensen & Ruback, 1983; Manne, 1965). It may, therefore, miss takeovers with considerably different motives. Also, the prediction can only be based on publicly available information at the time of the prediction process.

1.2 Structure and empirical approach

This thesis is divided into two foundation chapters, two empirical chapters and one application chapter. Chapter 2 provides a theoretical overview on takeover motives, aggregated takeover activity and takeover announcement returns. Chapter 3 presents the methodologies and hypotheses used in previous takeover prediction studies and discusses the suggested investment strategies based on these findings. The subsequent empirical analysis in chapter 4.1 develops a takeover prediction model based on eight hypotheses. Its prediction accuracy is tested in an out-of-sample test for 2011 and 2012 in chapter 5.1. Furthermore, an event study in chapter 4.2 examines the target announcement returns and the influence of the non-deal-specific factors of the prediction model on cumulative abnormal returns. This enables an interpretation of interdependencies between takeover probabilities and announcement returns. In chapter 5.2, the potential of investment strategies based on takeover prediction is tested for a long-only and long-short strategy over the last 17 years. The areas of application are finally discussed in chapter 6.

2. Theoretical Background

The following chapter gives the theoretical background for the subsequent chapters. First, a short overview of the terms takeover, merger and acquisition is given, followed by the motivations to do these transactions. Afterwards, theories of aggregated takeover activity are discussed in the various levels of factors, which determine the aggregated, industry- and firm-specific takeover activity. Subsequently, the returns especially for target shareholders following the announcement of a takeover are explained.

2.1 Definitions and takeover theories

2.1.1 Definition of takeovers

There are various definitions for the term takeover in the literature. Gaughan (2007, p. 12) states that the term takeover is often used in a broader sense to describe various types of transactions, sometimes just hostile takeovers, in other cases both friendly as well as hostile deals. A friendly takeover involves the acquirer's agreement with the current management of the target over various strategic and operational decisions for the future of the company (DePamphilis, 2010, p. 95). Being the more common way of proceeding, the friendly takeover often involves a standstill agreement, which prevents further investment in target's stock by the potential acquirer until a tender offer is negotiated with the target's management, which often includes a substantial premium on top of the previous stock price (DePamphilis, 2010, p. 21). In contrast to this, a hostile takeover does not involve agreement with the management. Hence, the acquirer can purchase shares on the open market and through a hostile tender offer, while circumventing the target's management (DePamphilis, 2010, p. 21). The success of this type of offer depends on the premium, the composition and investment horizon of the target's shareholders and on the target's corporate bylaws, which could include measures for takeover defenses (DePamphilis, 2010, p. 96).

Depending on the legal way of combining the target and the acquiring company, a takeover can constitute of either a merger or an acquisition. A merger unifies two or more firms into one, while the rest of the firms cease to exist in their former legal form (DePamphilis, 2010, p. 18; Gaughan, 2007, p. 12). In this context a statutory merger combines acquired firms into its former legal structure, whereas a statutory consolidation is the legal combination of two or more firms into a new firm, which did not exist before (DePamphilis, 2010, p. 18). In an acquisition on the other hand, the acquiring company takes control of the company, however the target company is not integrated into the legal structure of the acquirer, but exists as a legal subsidiary (DePamphilis, 2010, p. 20). In addition to the acquisition of stock, this can also involve assets of the target company. Furthermore, depending on the financial structure and the type of acquirer, an acquisition can also consist of a leveraged buyout, which involves the purchase of a company using high amounts of debt to finance it (DePamphilis, 2010, p. 20).

2.1.2 Motivations and drivers for mergers and acquisitions

The decision of the management of a firm to engage in mergers and acquisitions has various reasons. Trautwein (1990) summarizes the main theories on merger motives in the three categories of rational choice, process outcome and macroeconomic phenomena (see figure 2). Clearly, several motives can be involved in a takeover decision at the same time. The various theories will subsequently be explained.

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

Fig 1. Theories of M&A motives. The figure illustrates the motives for mergers and acquisitions divided into merger as rational choice, as process outcome and as a macroeconomic phenomenon.
Source: Own graphic, adapted from Trautwein (1990, p. 284).

Under the category of rational choices to the benefit of the bidder's shareholders, four main theories are subordinated. Hereby, *efficiency theory* sees synergies as the main reason for M&A. Trautwein (1990, p. 284) distinguishes three types of synergies: financial synergies, operational synergies and managerial synergies. Financial synergies lead to lower cost of capital by lowering systematic risk through diversification, increasing the company's size and the development of an internal capital market (Trautwein, 1990, p. 284). Operational synergies are realized through the combinations of business operations, which often leads to higher cost efficiency and knowledge transfer (Trautwein, 1990, p. 284). Furthermore, managerial synergies make use of the acquiring company's superior managerial skills to increase the target's performance (Trautwein, 1990, p. 284). Related to this is Jensen and Ruback's (1983) management competition model, which sees M&A as the capital market's disciplinary measures for poor decisions of management teams such as negative net present value projects. *Monopoly theory* mainly concerns the gain in market power that is achieved though mainly horizontal mergers. Chatterjee (1986) refers to this as collusive synergies. He states that these tend to generate more synergy value than operational or financial synergies and lead to a transfer of wealth from the consumers to the firms operating in the affected industry (Chatterjee, 1986, pp.120 & 136). Trautwein (1990, pp. 285-286) points out that even in conglomerate mergers, activities like product cross-subsidization, simultaneous limiting of competition in multiple markets or the deterioration of poten-

tial market entrants can be used to realize a gain in market power. *Raider theory* implies a wealth transfer from target shareholders to the corporate raider through e.g. greenmailing or excessive post-takeover compensation (Holderness & Sheehan, 1985, pp. 573 & 577; Trautwein, 1990, p. 289). However, Trautwein (1990) concludes that raider theory is rather unlikely and not empirically proven as target shareholders always gain following tender offers. *Valuation theory* is based on the idea that acquiring firm's managers have a better assessment of the target company's value than capital markets (Ravenscraft & Scherer, 1987; Trautwein, 1990, pp. 286-287). Ravenscraft and Scherer (1987, pp. 8-9) argue that even under the assumption of efficient capital markets, merger activity could be motivated by the belief of the existence and the subsequent exploitation of undervalued targets, as efficient market hypothesis only implies the incorporation of all public information in a company's stock price in its semi-strong form (Fama, 1970).

While the previously described theories involve mainly benefits for the acquirer's shareholders, *empire-building* describes M&A, which are mainly at the benefit of the acquirer's management. Empire-building theory indicates that M&A leads rather to the maximization of the manager's utility than the shareholder value (Trautwein, 1990, p. 287).

The concept of *process theory* builds on the idea that people are not capable of making rational decisions, when it comes to complex problems. This is based on Herbert Simon's theory of bounded rationality, which states that people rather find a satisfactory solution than an optimal solution (Simon, 1956). Simon bases this on the fact that they possess "limited information and limited computational facilities" (Simon, 1956, p. 129). Trautwein (1990, p. 289) points out that multiplication of the limited rationality of all involved persons leads to an irrational decision. Furthermore, highly optimistic assumptions by the management concerning potential synergies and the overall feasibility of potential gains from the merger or acquisition, which is the main idea of Roll's (1986) hubris hypothesis, can also influence the decision to do M&A.

Gort (1969) sees *disturbance theory* as the driver behind merger waves and hence merger activity in general. He argues that discrepancies in valuations increase the likelihood of takeovers. Further, this dispersion in valuations is affected by various types of economic shocks, such as new products or processes. In addition, Mitchell and Mulherin (1996) provided evidence of other types of shocks such as deregulation, changes in input costs or financial innovation, influencing takeover activity in the 1980s[1]. Another macroeconomic phenomenon that should be incorporated into the decision determinants of M&A is *mass behavior* in financial markets and investor sentiment, as especially economic booms and in its extreme form market manias, as well as economic recessions and financial crisis can have great influence on manager's decisions. The classic Kindleberger-Minsky model of financial crisis describes the typical development of a financial crisis in the four steps of displacement, boom, overtrading and revulsion/financial distress (Kindleberger & Aliber, 2011, pp. 27-33). Hereby, displacement can be seen as a shock similar to disturbance theory. Such a trigger creates market wide

[1] An overview of the various shocks and influence factors of merger waves is given in chapter 2.2.2.

optimism or even euphoria until the resulting boom and overtrading lead to a sudden market correction, which may even lead to panic (Kindleberger & Aliber, 2011, pp. 27-33). According to Shiller (1988), such mass behavior in financial markets also influences takeovers decisions, as relative to current investor sentiment a firm might be over- or undervalued for different reasons. Hence, behavioral factors can also have influences on many of the other theories such as valuation, empire-building and efficiency theory.

As the summary in figure 3 shows, a lot of the theories assume rationality of both the markets and the acquirer's managers making the decisions. However, this has to be seen under the condition that all assumptions contained in these theories are also rational.

		Markets	
		Rational	**Irrational**
Acquirer's Managers	**Rational**	– Efficiency theory – Monopoly theory – Empire-building theory	– Raider theory – Valuation theory
	Irrational	– Process theory / Hubris	– Mass behavior / market mania

Fig 2. M&A motives depending on rationality assumptions. This figure categorizes the drivers of M&A in a matrix of (ir)rational managers of the acquiring firms and (ir)rrational markets.
Source: Own graphic, adapted from Bruner (2004, p. 83).

2.2 Aggregated takeover activity – theories & influence factors

In order to get a general understanding of takeover activity and its influence factors, it is helpful to see takeovers and M&A in general in their aggregated form. Globe and White (1993) found empirical evidence of the existence of merger waves by fitting sine curves to the annual time series data of transactions from 1895 to 1989. In the United States, six waves can be identified since the end of the 19th century. In their classic corporate finance textbook "Principles of Corporate Finance", Brealey, Myers and Allen (2010, p. 908) still list the explanation for merger waves as one of the "10 Unsolved Problems in Finance", as it is often possible to find reasons to justify a specific transaction, but not the aggregated amount of transactions during a certain time period as opposed to another time. However, there are various theories, which give a possible explanation for merger waves. As Harford (2005, p. 532) points out, these theories concerning the creation of merger waves are mainly divided into the two fields of neoclassical theories and behavioral theories.

2.2.1 Theories on aggregated takeover activity and merger waves

The main neoclassical theories for takeover explanation are the theory of industry shocks or disturbance theory and q-theory. As already pointed out earlier, economic shocks trigger merger waves within an industry (Gort, 1969; Mitchell and Mulherin, 1996). Nelson (1959) finds a positive relationship between the share price level and M&A activity levels from 1885-1920. However, Harford (2005) argues this is only the case if "sufficient capital liquidity exists to accommodate the reallocation of assets" (Harford, 2005, p. 533). Q-theory in general assumes that the rate of investment increases with a company's Q[2] and investment should be higher than normally required if it is above 1 and lower if below 1 (Tobin & Brainard, 1997, p. 238). Jovanovic & Rousseau (2002) linked this theory to the topic of M&A, hypothesizing that mergers occur as a reaction to differences in Tobin's Q values among companies, as firms with high Qs take over firms with low Qs during merger waves.

The main concept in behavioral theories is overvaluation theory on a macro-level. It is seen as a determinant of merger waves, assuming that there are dispersions in valuation during times of booming stock markets. Shleifer and Vishny (2003) argue that managers of overvalued companies use their overvalued stock to take over real assets of undervalued targets. In line with the theoretical concept by Ravenscraft and Scherer (1987) that was described earlier, this implies that M&A activity is driven to a large extend by stock market valuation, assuming rational managers and irrational markets (Shleifer & Vishny, 2003, pp. 296-297). While Shleifer and Vishny (2003, p. 297) argue that the target managers accept the acquirer's overvalued equity because they have a short time horizon, Rhodes-Kropf and Viswanathan (2004, p. 2687) argue that they accept the bids due to an overestimation of synergies in a situation of rational decisions without perfect information. A study by Rhodes-Kropf, Robinson and Viswanathan (2005) shows further, that there is an aggregation of M&A when market valuations are relatively high compared to fundamental valuations. Breaking market-to-book ratios down into the three components of firm-specific error, time-series sector error and long-run value to book, they show that acquiring firms with high firm-specific errors take over firms with low firm-specific errors especially during times of positive time-series sector errors (Rhodes-Kropf, Robinson & Viswanathan, 2005, pp. 563 & 601).

2.2.2 Historical development of aggregated M&A activity - The six merger waves

As pointed out by Mitchell and Mulherin (1996), aggregated M&A activity is driven to a large extend by macroeconomic and industry shocks, which trigger the start or end of periods of great M&A activity. This is illustrated in an overview of the six merger waves with short descriptions of its individual influence factors and developments.

The first merger wave (1897-1904) was characterized by horizontal mergers and is known as the wave of mergers for monopoly. Mergers in various industries in the field of mining and manufacturing

[2] According to Tobin and Brainard (1997, p. 238), Q is defined as the ratio of "market valuation of reproducible real capital assets to the current replacement cost of those assets".

led to firms like Standard Oil, U.S. Steel or General Electric. The wave ended in 1904 with the stock market crash of 1904 and influenced by the enforcement of the Sherman Act under president Theodore Roosevelt, limiting mergers, which might lead to a monopoly. (Gaughan, 2007, pp. 30-36; Bruner, 2004, pp. 72-74).

The second merger wave (1916-1929) is described as a wave of mergers for oligopoly, including various vertical mergers, due to stronger anti-monopoly laws with the Clayton Act of 1914. While financing the deals under significant amounts of debt, the merger wave was brought to an end by the stock market crash of 1929, which led to a large decrease in business and investor confidence and emerged to the Great Depression. (Gaughan, 2007, pp. 36-39)

The booming economy in the 1960s brought about the third merger wave (1965-1969), which was characterized by conglomerate mergers of firms with diversified product portfolios. In contrast to the first two merger waves, the main sources of financing for the takeovers were equity and convertible bonds. With changing investor views on conglomerates and enforcement of takeover regulation for conglomerates in 1968, stocks of conglomerates were under significant pressure. Furthermore, the Tax Reform Act of 1969 limited financing via convertible debt. All of these factors led to a decrease in the stock markets and an end of the conglomerate merger wave. (Gaughan, 2007, pp. 40- 47)

Known as the wave of megamergers, the fourth merger wave (1984-1989) involved a very large amount of $100 million transactions compared to rather small and medium-sized deals in the previous wave. Triggered by deregulation, industries like airlines, banking and petroleum were subject to industry consolidations. In addition, corporate raiders and private equity firms acted as strong players, while financial instruments such as high yield bonds enabled them to use aggressive structures of debt to acquire companies. This changed when the junk bond market collapsed in the end of the 1980s and the phase of economic growth came to an end in 1989, leading to the end of the fourth merger wave. (Gaughan, 2007, pp. 53-39)

After the recession in 1990-1991, the fifth merger wave (c. 1992-2000) focused stronger on strategic deals than on the previously popular leveraged buyout and hostile takeovers. While including many large deals such as in the 1980s, the focus was particularly on the industries of banking and finance as well as communication and broadcasting, as the era of Internet businesses grew stronger and stronger towards the end of the 1990s. Moreover, the fifth merger wave was not only present in the United States, but large increases in M&A activity were also observed in Europe and Asia starting in 1998. (Gaughan, 2007, pp. 59-67)

The sixth merger wave (2003-2007) is characterized by its large share of cross-border, large horizontal transactions and leveraged buyout transactions, which were possible due to a period of low interest rates and a booming stock market and world economy (DePamphilis, 2010, p. 17). When investors started to sense the start of the financial crisis in 2007 and credit market lost its momentum, the strong deal activity of the sixth merger wave came to an end (Alexandridis, Mavrovitis & Travlos, 2012, p. 663).

Overall, the elaboration on the six merger waves shows a clear pattern of macroeconomic or industry-disturbances as the main influences on aggregated M&A activity, as mainly legal, financial and technological innovations as well as market sentiment triggered the start and end of the waves. Martynova & Renneboog (2006, pp. 2-3) point out that the European M&A market increased its activity tremendously during the fifth merger wave. This as not just fueled by transactions in the United Kingdom (UK), but also in Continental Europe, where the introduction of the Euro in the end of the 1990s triggered competitive pressure and with this intra-European cross-border M&A (Martynova & Renneboog, 2006, pp. 2-3).

2.3 Premiums and announcement returns in takeovers

In takeovers, the acquiring company generally pays a premium to the target shareholders. Assuming efficient capital markets with at least semi strong-from efficiency, the stock prices of both the target and the acquirer should adjust instantaneously, to incorporate all the new public information about a transaction (Fama, 1970). This includes the premium, form of payment and all other information relevant to investors.

2.3.1 Empirical evidence on takeover announcement returns

Empirical studies have shown that especially the target shareholders receive substantial positive abnormal returns in a given time period surrounding the announcement day of the announcement of a takeover offer. Studying a large sample of 3,688 completed transactions between 1973 and 1998, Andrade, Mitchell and Stafford (2001, p. 119) find that target shareholders received a significant 16.0% abnormal return in the three-day event window from one day before to one day after the announcement. When the event window is extended to 20 days before the announcement until the closing of the deal, which implies an average length of 142 days, Andrade, Mitchell and Stafford (2001, p. 110) find a significant cumulative average abnormal return of 23.8%. Table 1 shows a selection of empirical studies on announcement returns to the target firm shareholders in the United States (US) and Europe, including sample periods since the end of the 1920s.

An interesting fact included in the empirical study by Goergen and Renneboog (2004) on the European market is the difference in cumulative average abnormal returns (CAARs) between the United Kingdom (UK) and Continental Europe. Possible influence factors for this are the higher share of hostile takeovers and a stronger developed market for corporate control in the UK (Goergen & Renneboog, 2004, p. 39). Hence, one can argue that the UK market is much closer to the US market than to the Continental European market.

Table 1
Takeover returns for target firm shareholders

The table gives an overview of important empirical studies on takeover announcement returns to target firm shareholders in the United States and in Europe. If the event window is given in months, 21 trading days are assumed per month to make data comparable.

Study	Cumulative Abnormal Returns	Sample Period	Event Window (Trading Days)	Other Information
Empirical Evidence from the United States (US)				
Langetieg (1978)	+10.63% ***	1929-1969	(-126,0)	- Sample size: n=149 - US transactions - 90% of sample after 1950
Bradley, Desay & Kim (1988)	+31.77% ***	1963-1984	(-5,+5)	- Sample size: n=236 - Both acquirer and target are publicly listed US firms - Successful tender offers only
Jarrell & Poulsen (1989)	+28.99% ***	1963-1986	(-20,+10)	- Sample size: n=526 - Either acquirer or target is publicly listed US firms
Schwert (1996)	+30.1% **	1975-1991	(-42,+126)	- Sample size: n=1,174 - Target firms are publicly listed US firms - Successful tender offers only
Andrade, Mitchel & Stafford (2001)	+16.0% *** +23.8% ***	1973-1998	(-1, +1) (-20, Close)	- Sample size: n=3,688 - Both acquirer and target are publicly listed US firms
Empirical Evidence from Europe				
Franks & Harris (1989)	+23.3% ***	1955-1985	(-1, +20)	- Sample size: n=1,898 UK domestic transactions
Danbolt (2004)	+20.23% ***	1986-1991	(-42, +21)	- Sample size: n=514 - UK domestic transactions
Goergen & Renneboog (2004)	+12.96% *** +21.66% ***	1993-2000	(-2, +2) (-60, +60)	- Sample size: n=136 - 18 European countries incl. UK
	+17.42% *** +29.32% ***		(-2, +2) (-60, +60)	- Sample size: n=70 - UK targets
	+8.85% *** +14.82% ***		(-2, +2) (-60, +60)	- Sample size: n=66 - Continental European targets
Campa & Hernando (2004)	+8.90**	1998-2000	(-30, +30)	- Sample size: n=262 - 15 European countries incl. UK

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

Other influence factors on the level of the abnormal returns of the target shareholders can be separated into two different categories based on the acquirer's involvement. First, deal-specific factors like the type of payment (see, e.g. Huang & Walking, 1989)[3] or if the deal is cross-border or domestic (see, e.g. Harris & Ravencraft, 1991)[4]. Second, non-deal-specific factors related to the target, which are not influenced by the type of acquirer or the acquirer's decisions. Only few factors have been studied for non-deal-specific factors. Firm size is one factor that has been covered in the literature resulting in diverging findings of a positive (see, e.g. Melicher & Nielsen, 1978) or negative (see, e.g. Eckbo,

[3] Huang and Walking (1989, pp. 342-344) identify significantly higher target announcement returns for all-cash-deals compared to stock-offers.

[4] Harris and Ravencraft (1991, pp. 836-838) find that based on their US sample cross-border M&A transactions have higher announcement returns to target shareholders than domestic transactions.

2009) influence on target announcement returns. Furthermore, Eckbo (2009, p.156) finds a significantly positive influence of a target's book-to-market value that is higher than the industry median. Similarly, Walking and Edmister (1985, p. 32) find a negative influence of the market-to-book-ratio and also higher bid premiums for target firms with lower leverage. Lang, Stulz and Walking (1989) find a negative relationship between Tobin's Q and target shareholder returns. Another target-specific influence factor is profitability[5].

In contrast to announcement returns to target firm shareholders, the evidence is not so clear for the announcement abnormal returns for the acquirer's shareholders. The literature based on US studies shows returns in the range of slightly negative (see, e.g. Langetieg, 1978; Franks, Harris & Titman, 1991; Kaplan & Weisbach, 1992; Andrade, Mitchel & Stafford, 2001) to slightly positive cumulative average abnormal returns (see, e.g. Bradley, Desay & Kim, 1988; Jarrell & Poulsen, 1989; Schwert, 1996; Eckbo & Thorburn, 2000), with much lower statistical significance than for target shareholder returns. In his summary of various empirical studies from the 20th century, Bruner (2002) shows that negative, positive and zero abnormal returns are reported by each about one third of studies, while the majority of these returns are in the range of -5 to +5% of cumulative abnormal returns. The European studies (see, e.g. Franks & Harris, 1989; Campa & Hernando, 2004; Goergen & Renneboog, 2004) find low positive returns.

The CARs from takeover announcements can be separated into the two parts of run-up returns and markup returns, which Schwert (1996, pp. 162-163) defines as the two month period before the announcement of a tender offer and the time period from the announcement to delisting or six months after the announcement of the tender offer, respectively. Run-ups can have various reasons, as the stock markets try to predict the likelihood of a takeover, there might be news and rumors about a possible takeover or insiders use private information to earn a significantly large return from purchasing the target's shares before the public announcement of a takeover (Schwert, 1996, p. 166). Crawford and Lechner (1996) find that if the probability that a target will be acquired is already reflected in the share price, the reaction to the announcement and with it the markup return declines. Empirical evidence by Schwert (1996, pp. 162-165) shows that run-up returns are higher if news about possible takeovers are published or insiders are later accused of illegal trading on private information by the SEC. Findings of both Schwert (1996, p. 162) as well as Eckbo (2009, p. 151) show that run-up returns are realized as much as two months before the official announcement.

2.3.2 Risk of termination of takeover bid

As there are still various obstacles, including the approval of the Federal Trade Commission and the Department of Justice in the US or the European Commission in the European Union, there is still some uncertainty concerning the closing of the deal after the announcement of a tender offer. Schwert

[5] In a study of US bank merger premiums, Palia (1993, p. 99) finds a positive influence of the target's return on assets.

(1996, p. 162) finds that there is an immediate gain to the target firm shareholders after the announcement and the share price continues to rise for successful deals to reach the price of the tender offer at the time of the deal's closing. For unsuccessful deals however, the CAR disappears over the year after the tender offer announcement to reach the pre-bid share price (Schwert, 1996, p. 162; Davidson, Dutia & Cheng, 1989). Furthermore, the average CARs of unsuccessful deals are already 4.3% lower than for successful deals in the period from day -42 to day -1, which can be interpreted as a lower closing probability prediction by the market (Schwert, 1996, p. 164). The CAR after the announcement of a takeover can be seen as $\mathrm{CAR}(-1,1) = \mathrm{CAR_s}\pi(x) + \mathrm{CAR_f}(1 - \pi(x))$, where π is the probability of a successful completion of the deal with characteristics x_j, and CAR_s and CAR_f are the target firm shareholder's gains in case of a successful offer and a failing offer, respectively (Betton, Eckbo & Thorburn, 2010, p. 81). To avoid the uncertainty that a deal does not close successfully after the announcement of a tender offer, there is a possibility for the shareholders to sell their shares on the stock market shortly after the announcement, where e.g. merger arbitrageurs speculate on the outcome of the takeover. Hence, they receive insurance for the transaction completion risk, by selling their shares early (Baker & Savasoglu, 2002, pp. 91-92). This involves a special investment strategy in which the merger arbitrageurs buy the target's shares at the post-announcement share price, betting on the probability of a successful transaction closing to benefit from the arbitrage spread, which is the difference between the post-announcement price and the offer price (Betton, Eckbo & Thorburn, 2010, p. 94). Baker and Savasoglu (2002) find that a monthly risk-adjusted return of 0.6-0.9% can be generated by merger arbitrageurs using this strategy.

3. Literature Review

After the introduction to general theories on takeover motives and M&A activity, this section will give an overview of the literature on takeover prediction and the assessment of takeover probabilities. First, the empirical studies on takeovers are presented in terms of their methodological development as well as the hypotheses and prediction factors used in the different models. Second, the different investment strategies used to generate abnormal returns are discussed. Finally, the research goal of this thesis is laid out.

3.1 Prediction of takeovers

The prediction of takeovers, using publicly available information has been subject of various studies since the early 1970s. Some of these studies are motivated by a potential profit, while trading based on these predictions, as target shareholders earn a substantial market-adjusted return in the time frame around the announcement of a takeover[6]. However, the market does not show any signs of an early prediction success in form of CARs earlier than 2 months before the announcement of the transactions, as stated earlier based on run-up-returns (Schwert, 1996; Eckbo, 2009). Palepu finds similar results (1986, p. 3), pointing out that the prediction-accuracy by the stock market is not very good even three months prior to the announcement of a takeover. Jensen and Ruback (1983) state, "it is difficult, if not impossible, for the market to identify future target firms" (p. 29). Hence, if a prediction model is found that enables a successful prediction of takeover targets, it should be possible to earn a positive market-adjusted return buying these targets more than two months before the announcement of a takeover.

In the last decades, there have been various empirical studies trying to predict takeover targets, while analyzing public information using statistical models. The geographical focus of these studies has mainly been the United States (see, e.g. Simkowitz & Monroe, 1971; Stevens, 1973; Harris, Stewart, Guilkey & Carleton, 1982; Dietrich & Sorensen, 1984; Palepu, 1986; Ambrose & Megginson,1992; Cudd & Duggal, 2000; Espahbodi & Espahbodi, 2003; Cremers, Nair & John, 2009) and the UK (see, e.g. Barnes, 1990/1999; Powell, 1997/2001/2004). Furthermore, empirical studies have been published for Canada (see, e.g. Belkaoui, 1978; Rege, 1984), Australia (see, e.g. Castagna & Matolcsy, 1976) and Greece (see, e.g. Tsagkanos, Georgopoulos & Siripoulos, 2006). Only Brar, Giamouridis and Liodakis (2009) have studied the European market including several countries.

3.1.1 Development of methodologies over time

In the empirical studies, different methodologies have been used to identify the relevant variables of takeover targets. Many of the early predictions were based on the methodologies used to predict bank-

[6] The empirical studies presented in chapter 2.3.1 show returns to the target shareholders of 10-32%.

ruptcies up to four years in advance, which are methodologically similar (Barnes, 1990, p. 73). Harris, Stewart, Guilkey and Carleton (1982) used a probit model to specify characteristics of takeover targets. Stevens (1973) as well as Barnes (1990) use multiple discriminant analysis to distinguish targets from non-targets. Dietrich and Soerensen (1984) first used logistic regression for the prediction of takeover targets after this method had previously been used in the prediction of bankruptcies (see, e.g. Ohlson, 1980). This had the advantage of not only being able to classify targets and non-targets, but also the probability of an event (Dietrich & Sorensen, p. 398; Ohlson, 1980, p. 112). Palepu (1986), as one of the most influential studies in this field also suggested the use of a logistic regression or logit probability model. In his study he focuses on methodological errors in previous empirical studies on the prediction of takeovers and on the right use of cutoff probabilities (Palepu, 1986). Many of the later studies used his work as a base for their analysis. Barnes (1999) suggested the profit-maximization criterion as a methodological improvement to Palepu's (1986) logit model, which included a criterion of error minimization, arguing that this is more appropriate if the goal of a positive abnormal return is pursued. Tsagkanos, Georgopoulos and Siripoulos (2006) use a conditional logit model, which indicates a higher predictive ability than a regular logit regression model. Another methodological approach was e.g. the use of a recursive partitioning method by Espahbodi & Espahbodi (2003). Table 2 provides an overview of the most relevant studies on takeover prediction.

Table 2
Takeover prediction studies

The table shows the most relevant empirical studies on takeover prediction in chronological order, illustrating the development of the employed methodology, region and data samples.

Study	Methodology	Geographic region	Sample Period	Data
Simkowitz & Monroe (1971)	Multiple discriminant analysis	USA	1968	23 targets and 25 non-targets
Stevens (1973)	Multiple discriminant analysis	USA	1966-1970	40 targets and 40 non-targets
Harris, Stewart, Guilkey & Carleton (1982)	Univariate probit model	USA	1974-1977	106 targets and 1200 non-targets
Dietrich & Sorensen (1984)	Logit regression	USA	1969-1973	30 targets and 59 non-targets
Palepu (1986)	Logit regression	USA	1971-1979	163 targets and 256 non-targets, listed on NYSE or AMEX
Barnes (1990)	Multiple discriminant analysis	UK	1986-10/1987	90 targets and 90 non-targets, UK listed companies
Ambrose & Megginson (1992)	Logit regression	USA	1979-1986	169 targets and 267 non-targets, listed on NYSE or AMEX
Powell (1997)	Logit regression	UK	1984-1991	411 targets and 532 non-targets
Barnes (1999)	Logit regression	UK	1991-1993	82 targets and 82 matched non-targets
Cudd & Duggal (2000)	Logit regression	USA	1987-1991	108 targets and 235 non-targets listed on NYSE or AMEX
Powell (2001)	Logit regression	UK	1986-1995	471 targets and 471 non-targets listed on London

				Stock Exchange
Espahbodi & Espahbodi (2003)	Recursive partinioning, logit, probit & multiple discrimant analysis	USA	1993 - 1997	133 targets and 385 non-targets
Powell (2004)	Logit regression	UK	1986-1995	471 targets (390 friendly, 81 hostile) and 9,420 non-target data points over 10 years
Tsagkanos, Georgopoulos & Siripoulos (2006)	Conditional logit regression & logit regression	Greece	1995-2001	56 targets and 305 non-targets
Cremers, Nair & John (2009)	Logit regression	USA	1981-2004	5,457 announced and completed targets and 78,295 non-targets; 2,813 completed deals
Brar, Giamouridis & Liodakis (2009)	Logit regression	Europe	1992-2003	Estimation sample: 262 targets and 722 non-targets, excl. financial sector

Many of the early empirical studies claimed to get prediction rates of 60-90% (Palepu, 1986, p. 3; Barnes, 1999, p. 283). However, Palepu (1986) points out the various methodological flaws of these earlier studies, so it is obvious that many of these results are overstated. Hence, the focus of the following sections lies mainly on the empirical studies that were published after the influential paper by Palepu. He criticizes for example the use of non-random equal share samples for the model estimation and the use of arbitrary cutoff probabilities for the classification of targets and non-target (Palepu, 1986, p. 4).

In order to predict if a company will be a target or not, it is necessary to find a way to classify the firms according to their takeover probability. Comparing the takeover probability of a specific firm with a predefined cutoff probability, allows the classification into targets and non-targets, if the takeover probability is above or below the threshold, respectively. Palepu (1986, pp. 11-12) criticizes previous studies for using arbitrary cutoff probabilities of e.g. 50% to derive a classification decision. He suggests deriving the optimal cutoff probability as the intersection between the probability density functions of takeover probability for targets and non-targets (Palepu, 1986, pp. 14-15).

3.1.2. Prediction factors and hypotheses used in empirical studies

As the prediction model is always only as good as the prediction variables it is based on, it is important to understand the various influence factors that should be included to achieve a successful prediction result. Palepu (1986, p. 16) points out that many of the earlier empirical studies did not base their chosen variables on pre-specified variables, but integrated variables based on their statistical significance step by step after testing a large number of variables (see, e.g. Simkowitz & Monroe, 1971). However, he points out that this leads to a "statistical 'overfitting' of the model to the sample at hand" (Palepu, 1986, p. 16), which is not a clean method of finding a general explanatory model that explains takeover probability.

Generally, the hypotheses for takeover prediction are derived from the market for corporate control as a research area, seeing takeovers as a disciplinary procedure for underperforming management (see, e.g. Jensen & Ruback, 1983; Manne, 1965). Many of the hypotheses used in the various studies are based on Palepu (1986), who suggests nine independent variables to determine the acquisition likelihood based on the six hypotheses inefficient management, growth-resource mismatch, industry disturbance, size, market-to-book ratio and price-earnings ratio. The various hypotheses and the associated variables used to predict takeovers in previous empirical studies presented in the following section are divided into the subsections of firm- and industry-specific as well as macroeconomic hypotheses. It can be argued that macroeconomic factors, both neoclassical and behavioral, as well as industry-specific factors have a major influence on the level of aggregated M&A activity, whereas firm- and industry-specific takeover probabilities at a specific point in time are mainly influenced by firm-specific and industry-specific factors (see figure 4). The takeover prediction literature provides a large number of hypotheses and possible variables on a firm-level, but rather restricted number of industry and macroeconomic determinants.

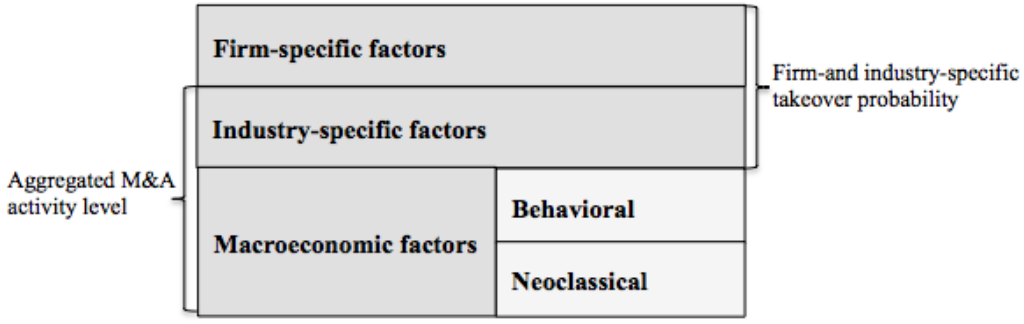

Fig 3. Categorization of influence factors for takeover prediction. A summary of the various influence factors on aggregated M&A activity and takeover probability.
Source: Own graphic.

3.1.2.1 Firm-specific hypotheses for takeover prediction

This section will give an overview on the main hypotheses used for takeover prediction models. As many of the studies are based on Palepu (1986), most of the studies base their models on similar hypotheses as the six he used, but extend them by new hypotheses or other variables. Subsequently, the hypotheses inefficient management, firm size, growth-resource mismatch and undervaluation will be explained and further hypotheses used in empirical studies on takeover prediction will be introduced.

Jensen and Ruback's (1983) management competition model builds the foundation for the *inefficient management hypothesis*. It assumes that underperforming management might increase the probability that a company will be acquired to use managerial synergies to generate value (Jensen & Ruback, 1983). This hypothesis is used in almost all of the empirical studies on takeover prediction. In order to specify this hypothesis, Palepu (1986, p. 16) suggested the use of average excess return on the firm's share performance and the shareholder's return on equity as a proxy for accounting profitability.

The *firm size hypothesis* suggests a negative relationship between the size of the target and its takeover likelihood, justified with post merger integration costs and costs related to takeover defense, which are both likely to rise substantially with target size, so the number of potential acquirers decreases (Palepu, 1986, p. 18). The *growth-resource mismatch hypothesis* assumes a discrepancy between the financial resources available for a firm and their growth, as both low-growth, resource-rich firms and high-growth, resource-poor firms are likely acquisition targets (Palepu, 1986, p. 17). This is integrated into the model by using a growth-resource dummy variable based on average growth rate as an indicator for growth, net liquid assets as an indicator for liquidity and debt-to-equity ratio as an indicator for leverage. Moreover, the *undervaluation hypothesis* combines both *market-to-book (M/B) hypothesis* and *price-earnings hypothesis*, as defined by Palepu (1986), since both concepts have similar motivations. M/B hypothesis assumes that firms with low M/B ratios are more likely to be a takeover target, which was proven empirically in a study by Rhodes-Kropf, Robinson and Viswanathan (2005), showing that there is a tendency for firms with high M/B to acquire firms with low M/B. Price-earnings hypothesis is based on the idea that firms with low price-earnings (P/E) ratios are more likely to be acquired, as acquiring companies with high P/E ratios expect the market to value the newly acquired earnings with the same high P/E multiple as before, leading to a capital gain (Palepu, 1986, p. 18). This result is also found by Brar, Giamouridis and Liodakis (2009, pp. 435-436), who find that lower P/E multiples and higher dividend yields have positive influence on the takeover likelihood of a company. The latter could be reasoned by Smith and Watts' (1992) argumentation that firms with low dividend payments have higher growth options, so the takeover likelihood is expected to be lower. However, one could also argue that this relationship concerning growth options links directly to Palepu's (1986) growth-resource mismatch hypothesis in the case of firms with low growth and large amounts of financial resources.

Other studies add to the basic hypotheses described above. A factor integrated into some empirical studies is *leverage*, which is mentioned by Dietrich and Sorensen (1984) as well as Brar, Giamouridis and Liodakis (2009), but only found significant by Cremers, Nair and John (2009, p. 1421) in their sample of all announced but not the completed deal sample. However, Brar, Giamouridis and Liodakis (2009, p. 438) find that *liquidity* measured as cash-to-total-capital ratio is significantly lower for takeover targets, which could be linked to a strong influence of leveraged buyout firms. Furthermore, Ambrose and Megginson (1992) study the influence of the share of tangible assets on the balance sheet, finding a statistically significant difference. Ambrose and Megginson (1992) further examine the influence of variables related to the ownership structure (e.g. institutional and insider shareholding) and takeover defense (e.g. poison pills or classified boards), of which however only the percentage change in institutional shareholdings is statistically significant.

Brar, Giamouridis and Liodakis (2009) suggest short-term technical factors as another field of influence factors for takeover prediction. They find that both price momentum on a three-month period and the trading volume measured as a percentage of free-float market capitalization are significantly

different for takeover targets (Brar, Giamouridis and Liodakis, 2009, p. 438). Moreover, they find that not leverage, but the level of liquidity measured as cash-to-total-capital ratio is significantly lower for targets than for non-targets (Brar, Giamouridis and Liodakis, 2009, p. 438).

Table 3 provides an overview of the hypotheses and variables employed in the most important empirical studies of the takeover prediction literature.

Table 3
Overview of firm-specific hypotheses and variables used for takeover prediction

This table summarizes the various firm-secific hypotheses used in empirical studies on takeover prediction and the respective variables used for their specification. The expectation of the relation to takeover likelihood is stated as the expected sign, where "+" indicates an increase in takeover likelihood and "-" a decrease.

Hypotheses	Variables	Expected sign[a]	Empirical study
Inefficient Management	- Return on equity	-	Palepu (1986); Brar, Giamouridis & Liodakis (2009)
	- Average excess return	-	Palepu (1986); Ambrose & Megginson (1992)
	- Operating profit / capital employed	-	Powell (2001)
	- Tobin's Q	-	Cremers, Nair & John (2009); Brar, Giamouridis & Liodakis (2009)
	- Profit before tax / sales - Profit before tax / shareholder's equity - Growth of profit before tax (L3Y) - Price / earnings - Av. dividend (L3Y) / shareholders equity - Dividend growth (L3Y)		Barnes (1999)
	- Profit margin (&growth)** - Profits / capital - Asset turnover (& growth) - Market share - Return on sales - Return on capital - Sales growth*	-	Brar, Giamouridis & Liodakis (2009)
Firm size	- Net book assets	-	Palepu (1986); Ambrose & Megginson (1992); Powell (2001)
	- Market capitalization**	-	Dietrich & Sorensen (1984); Barnes(1999); Cremers, Nair & John (2009); Brar, Giamouridis & Liodakis (2009)
	- Sales*** - Number of employees***	-	Brar, Giamouridis & Liodakis (2009)
Growth-financial resource mismatch	- Growth-resource dummy (Based on sales growth, liquidity and leverage)	+	Palepu (1986); Ambrose & Megginson (1992); Powell (2001)
	- Sales / total assets - Total renumeration / sales - Sales growth (L2Y) - Sales growth (L3Y) - Current assets / current liabilities - Current assets - current liabilities / total assets		Barnes (1999)
Undervaluation	- Price / earnings***	-	Dietrich & Sorensen (1984); Palepu (1986); Ambrose & Megginson (1992); Brar, Giamouridis & Liodakis (2009)
	- Market / book	-	Palepu (1986); Ambrose & Megginson (1992); Powell (2001)
	- Market cap / shareholder's equity		Barnes (1999)

	- Dividend yield*** - Price / book	+/-	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	+	Brar, Giamouridis & Liodakis (2009)
Liquidity	- Cash to capital***	-	Brar, Giamouridis & Liodakis (2009)
Tangible assets	- Tangible fixed assets / total assets		Ambrose & Megginson (1992); Powell (2001)
Ownership structure	- Number of institutional managers following firm - % of institutional shareholding - Change in institutional shareholding - % of officer and director shareholding		Ambrose & Megginson (1992)
	- Dummy if instiutional blockholder exists		Cremers, Nair & John (2009)
Takeover defenses	- Poison pill - Antitakeover charter amendments - Blank-check preferred-stock - Classified boards - Fair-price requirements - Supermajority requirement - Dual-class recapitalizations - Voting right restrictions		Ambrose & Megginson (1992)
Momentum	- Price momentum (3 month)*** - Price momentum 12 month) - Average trading volume as % of market cap *** - Analyst earnings revisions	+/-	Brar, Giamouridis & Liodakis (2009)
Age	- Age of firm since listed - Age dummies	-	Brar, Giamouridis & Liodakis (2009)
Barrier to entry	- Minimum efficient scale (MES) - Market share - Herfindahl index	-	Brar, Giamouridis & Liodakis (2009)
Rumors	- Annual no. of articles teporting takeover speculation	+	Brar, Giamouridis & Liodakis (2009)

*, ** and *** show statistical significance at the 10%, 5%, and 1%-level respectively in the study of Cremers, Nair and John (2009) or Brar, Giamouridis and Liodakis (2009)

3.1.2.2 Industry-specific hypotheses for takeover prediction

As mentioned earlier, the industry disturbance hypothesis is based on Gort's (1969) as well as Mitchell and Mulherin's (1996) assumption of the influence of aggregated merger activity by economic shocks. This leads to the integration of an industry dummy variable, which indicates the presence of an industry shock through previous M&A activity in the same industry during the prior year (Palepu, 1986, pp. 17-18). Specifically, Palepu (1986) bases this dummy variable on the occurrence of an acquisition within a firm's four-digit standard industrial classification (SIC) code, whereas Brar, Giamouridis and Liodakis (2009) use the MSCI 24 industry group classifications and Cremers, Nair and John (2009) base it on the Fama-French 48 industry classifications.

3.1.2.3 Macroeconomic hypotheses for takeover prediction

A field of variables that is not covered as much in takeover prediction models is macroeconomic variables. It can be assumed that these mainly influence aggregated takeover activity as a worldwide or

country-specific macroeconomic basis for takeover probabilities. Bruner (2004, pp. 91-96) argues that besides firm- and industry-specific factors, M&A activity in general is mainly influenced by macroeconomic and sector conditions (e.g. GDP, interest rates, exchange rates, government fiscal policy, central bank monetary policy, current position in the macroeconomic cycle), equity and debt capital markets (e.g. debt yields, risk premiums, credit ratings, multiples, betas) and customers behavior (e.g. price elasticity of demand). A study by Becketti (1986) finds that about one third of variation in US takeover activity from 1960 to 1980 was related to macroeconomic factors. As already seen for theoretical concepts of merger activity these factors can be distinguished into neoclassical factors and behavioral factors, depending on the rationality assumption behind it.

Neoclassical factors are given for each geographic or economic region and define the market in which potential targets operate. Melicher, Ledolter and D'Antonio (1983) argue that there are only weak positive correlations between the (macro-) economic situation of a country and M&A activity. However, there are also macroeconomic factors, which were found to be indicators of global M&A activity. Gross national product (see Steiner, 1975; Chung & Weston, 1982) as well as gross domestic product (see Globe & White, 1988) are found to be positive influence factors of aggregated takeover activity in US samples. Interest rates are found to have a negative correlation (see e.g. Becketti, 1986; Ploncheck & Sushka, 1987; Yagli[7], 1996; Globe & White, 1998) with merger activity. Other factors that are studied in the literature are unemployment rate[8] and capacity utilization rates[9]. Qualitative factors are e.g. related to country specific legal conditions that have an influence on corporate governance issues (see, e.g. Rossi and Volpin, 2004).

Behavioral factors include market-related variables, which are influenced by irrational decisions. One example for this is market sentiment, which is suggested by Brar, Giamouridis and Liodakis (2009), who integrate a dummy variable with a value of 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" (Brar, Giamouridis & Liodakis, 2009, p. 439).

3.2 Earning abnormal returns from takeover probability prediction

Numerous empirical studies employ prediction models to forecast the probability of takeovers, however only few have tested if these are able to achieve abnormal returns by investing in the predicted targets. Powell (2001, p. 993) points out that next to the investment perspective that derives an investment strategy from these predictions, there is also a policy perspective, which primarily improves our understanding of takeover motives, as a reason for modeling takeovers. The following chapter

[7] Yagli (1996) finds a positive correlation for cash transactions, but a negative correlation for equity transactions.

[8] Ploncheck & Sushka (1987) find a negative relationship between unemployment rates and M&A activity.

[9] Becketti (1986) observes a significant positive influence of changes in capacity utilization on takeover activity as acquirers grow their capacities externally through M&A.

presents the different investment strategies based on takeover prediction models and their success in terms of positive market-adjusted returns that one can generate from these.

3.2.1 Theoretical aspects of abnormal returns from takeover prediction

As pointed out in chapter 2.3.1 the target shareholders can earn significant cumulative abnormal returns during the time period around the announcement of a takeover. Hence, the successful prediction and the investment in the target during the pre-announcement period can enable the investor to profit from this. However, even though a model might be able to successfully predict takeover targets, this does not imply that a positive market-adjusted return can be generated based on this, since other market participants might identify the same target, which might lead to early adjustments of the share price (Powell, 2001, p. 994). Palepu (1986, p. 13) shows that under the assumption of an efficient market the current stock price S of a company is

$$S = q\,S_1 + (1-q)\,S_2 \qquad (1)$$

, assuming public knowledge of q (market's assessment the firm's takeover probability), S_1 (stock price if the firm becomes a target) and S_2 (stock price if the firm does not become a target). Hence, the expected payoff assuming a payoff of $C_1 = S_1 - S$ in case of a target and $C_2 = S_2 - S$ in case of not being a target is $q\,C_1 + (1-q)\,C_2 = 0$. This shows that one can only make a return from using takeover prediction, if the predictive power of the model is better than the market's assessment of the firm's takeover probability q at the time of the prediction.

3.2.2 Portfolio construction and abnormal returns in empirical studies

One of the first empirical studies testing the ability to generate abnormal returns based on a takeover prediction model is Palepu (1986). He defines the optimal cutoff probability, as described earlier, and then invests in a portfolio consisting of all firms that are predicted targets as they have takeover probabilities that exceed the optimal cutoff probability (Palepu, 1986, pp. 27-30). Based on the cutoff probability of 0.112, Palepu (1986) defines 625 targets and 492 non-targets for the out-of-sample test of 30 targets and 1087 non-targets in 1980. Even though 80% of the targets are successfully predicted this still includes a large type II error of 55.3% as only 24 of the 625 predicted targets are actually targets (Palepu, 1986, pp. 26-27). Palepu (1986) forms an equally weighted portfolio of the 625 predicted targets to test their ability to generate an abnormal return over a holding period of 250 trading days starting on the 2nd of January 1980. As a consequence of the included 601 falsely predicted targets, the cumulative excess return generated by Palepu's portfolio is only -1.62%, which is even smaller than the portfolio of predicted non-targets with a CAR of -1.51% (Palepu 1986, p. 29). However, the CAR of the subgroup of the 24 actual targets that were included in the predicted targets generated a significant CAR of 20.98%. The six targets included in the predicted non-targets had a CAR of 36.24%, which is – depending on the sample - not necessarily a signal for a higher CAR because of a lower takeover prediction by the market, but it could be an indication for it. Overall, Palepu's in-

vestment strategy shows that it is not possible to generate a positive CAR by investing in a portfolio of all the predicted targets. Hence, the challenge is to find a portfolio, which helps to generate a positive CAR as it contains a higher percentage of actual targets.

If one assumes that the return is mainly generated by takeover bids, the return on the takeover target portfolio will only exceed the market return, if the percentage of actual targets within the predicted targets is large enough, so that the abnormal returns generated by the actual targets have an impact on the entire portfolio. Powell (2001, p. 994) points out that the large number of non-targets in the portfolio, which have CARs around zero, dilute the actual targets' positive CARs. Furthermore, Palepu (1986) assumes that the costs of type I (target incorrectly classified as non-target) and type II (non-target incorrectly classified as target) errors are equal and constant, which is according to Powell (2001, p. 999) rather unrealistic since the "gains to target firms prior to takeover far exceed those to firms not taken over". Hence, the costs for a type I error are larger than for a type II error (Powell, 2004, p. 52). Powell (2001, pp. 999-1000) suggests the use of an approach that maximizes the share of actual targets within the prediction portfolio instead of Palepu's (1986) approach of minimizing the number of misclassifications. As a consequence, Powell (2001, p. 1000) proposes the determination of the cutoff probability by constructing ten portfolios, which are analyzed for their differences in the concentration of targets they include. The decile with the highest concentration ratio sets the cutoff probability as the first takeover probability in that portfolio (Powell, 2001, p. 1000). Despite all the adaptions in Powell's model, the market-adjusted return is at a significant -11%, which is even worse than the performance using a method similar to Palepu (1986) (Powell, 2001, p. 1007). The size-adjusted model generates an insignificant CAR of -4% (Powell, 2001, p. 1007). This is done, since according to the firm size hypothesis, takeover targets are significantly smaller than the average market size. In a later study based on the same data, Powell (2004) finds only one scenario, which generates a significantly positive abnormal return, while using a multinomial model predicting only hostile targets. Over a 12-month holding period, the portfolio of 117 firms that resulted in 7 targets and 110 non-targets, generated a buy and hold abnormal return of 7% (Powell, 2004, p. 63). The positive return is caused by positive abnormal returns of the non-targets in the portfolio. Powell (2004, p. 63) gives the larger size of hostile targets as a reason for this, which leads to a lower probability of financial distress compared to friendly targets.

In their study the prediction of takeovers in the European market, Brar, Giomouridis and Liodakis (2009) choose Powell's (2004) methodology of selecting the optimal cutoff probability, based on dividing the ranked estimation sample in 10 deciles and choosing the cutoff probability of 0.41 from the portfolio with the highest concentration ratio (Brar, Giamouridis & Liodakis, 2009, p. 445). Their strategy of investing in the top 10 % takeover likelihood firms results in a market-adjusted return of 8.5% relative to a size-matched control portfolio, assuming a holding period of one month and monthly rebalancing (Brar, Giamouridis & Liodakis, 2009, p. 447).

Cremers, Nair and John (2009) use a long-short portfolio, which buys the firms with the highest takeover likelihood and shorts the firms with the lowest. Using this approach, they find that a portfolio that buys the quintile with the highest and shorts the quintile with the lowest takeover likelihood generated a significant annualized abnormal return of 11.77% in the time period from 1981-2004 (Cremers, Nair & John, 2009, p. 1424). The same takeover-spread portfolio approach with a use of deciles generated an even higher return of 21.67% with a t-stat of 10.0 (Cremers, Nair & John, 2009, p. 1424). Their study bases these returns on the fact that returns for firms with higher takeover exposure are higher and show that the created takeover factor adds additional explanatory power to four-factor Fama-French(1992) and Carhart (1997) model (Cremers, Nair & John, 2009, pp. 1409-1411). Hence, the returns for high takeover probability firms are not necessarily just generated due to takeover bids, but also because of their higher exposure to takeovers.

Table 4
Overview of achieved CARs from takeover prediction

This table summarizes the results of empirical studies on takeover prediction, which integrated a portfolio strategy and calculation of returns adjusted for the market return or other factors.

Study	Cumulative abnormal return on portfolio	Investment period	Other information
Palepu (1986)	-1.62%	250 trading days	Investment in a portfolio of all 625 predicted targets of the out-of-sample test of 1117 firms in 1980.
Powell (2001)	-11%***	12 months	Investment in portfolio of 216 predicted targets of the out-of-sample test of 1000 firms in 1996.
Powell (2004)	+7%	12 months	Investment in a portfolio of 117 predicted hostile targets of the out-of-sample test of 1000 firms in 1996. 7 targets; 110 non-targets.
Brar, Giamouridis & Liodakis (2009)	+8.5%**	1 month	Investment in portfolio of upper 10% takeover likelihood firms with monthly rebalancing.
Cremers, Nair & John (2009)	11.77%***	12 months	Takeover-spread portfolio, buying the quintile (decile) of firms with the highest and shorting the quintile (decile) with the lowest takeover likelihood. In-sample test for 1981-2004 (announced and completed returns
	21.67%***	12 months	

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

3.3 Interim findings and classification of thesis

After outlining the relevant takeover motives, merger theories and literature on takeover prediction, this chapter summarizes the findings up to this point. Furthermore, it defines the research gap, which builds the foundation for the contribution of this thesis to the existing literature.

3.3.1 Interim findings

Chapter two summarized the theoretical knowledge on merger motives, aggregated takeover activity and takeover returns. Based on the work by Trautwein (1990), mergers & acquisitions are mainly caused first, by rational choice to the benefits of bidder's shareholders or managers, second, by process outcome and third, as a consequence of a macroeconomic phenomenon. The specific theories related to these categories are for example efficiency, monopoly, valuation, empire-building and disturbance theory. According to the literature, aggregated takeover activity is influenced by neoclassical theories, such as industry disturbance theory and Q-theory, as well as behavioral theories, mainly in the form of overvaluation theory on a macroeconomic level. Empirical evidence on takeover announcement returns finds returns to the target shareholder of 10 to 32% during various periods around the announcement day of a transaction. These findings give a theoretical base for both influence factors of takeovers and the returns they generate for the target's shareholders.

The third chapter introduced the methods, hypotheses and variables used in previous empirical studies on takeover prediction and their success in both predictive accuracy and generation of abnormal returns using takeover prediction. Having mainly studied the US and UK markets since the 1970s, the takeover prediction literature methodologically grew out of the prediction of bankruptcies. Since the influential study by Palepu (1986), the main process used for takeover prediction is a logit regression approach based on his suggested hypotheses of inefficient management, firm size, growth-resource mismatch, undervaluation and industry disturbance. Subsequent studies add further markets, factors or methods, but are mostly based on Palepu's (1986) paper related to the market for corporate control. Takeover prediction as a source for investment strategies was only covered by few studies. As Palepu's (1986) approach of an investment in all expected takeovers fails to generate abnormal returns, alternative methods such as decile portfolios for firms with the highest takeover probability were introduced by Powell (2001) and employed by Brar, Giomouridis and Liodakis (2009) and Cremers, Nair and John (2009). The latter developed a takeover factor, which explains cross-sectional returns beyond the classic four-factor Fama-French (1992) and Carhart (1997) model, assuming that firms with higher takeover exposure have higher returns. Hence, returns from takeover prediction are not necessarily just generated by the actual takeover of firms but also the exposure to it.

3.3.2 Research gap and contribution of thesis

This thesis contributes to the existing literature in three main points.

First, the selection of the estimation sample for 1996-2010 incorporates the 5th and 6th M&A wave into the prediction model, which gives new insights for the prediction of European takeover targets compared to older studies[10]. Gaining momentum in the end of the 1990s, the European M&A market,

[10] The newest and only study for the European market is by Brar Giomouridis and Liodakis (2009), using a sample from 1992- 2003. Powell (2004) studies the UK only in a sample from 1986-1995.

especially outside the UK, underwent various changes (see, e.g. Martynova and Renneboog, 2006, pp. 2-3). This changing environment could go along with differences in takeover prediction factors.

Second, a conditional logit regression model is used for the estimation of a takeover prediction model. The approach is based on the influential empirical study by Palepu (1986). However, the matching of random non-target observations to each target observation by year and 4-digit standard industry classification (SIC) code enhances the predictive ability of the model, as only matching observations are compared.

Third, this thesis examines differences in takeover prediction success for potential targets in the United Kingdom and Continental Europe[11]. This is of relevance, as it is often assumed that the UK is closer to the US market in its behavior and reactions to takeovers than to the rest of Europe[12]. Subsequently, it can be investigated if there are differences between these two regions in the potential to generate returns through investment strategies based on takeover prediction.

3.3.3 Approach, goals and limitations

In order to investigate possibilities of takeover prediction in the UK and Continental Europe, a takeover prediction model based on the six hypotheses of Palepu (1986) and selected additional hypotheses is estimated. Hereby, the focus is on firm- and industry-specific variables to derive takeover probabilities, as these are seen as more relevant for prediction of specific takeover targets. The goal is to identify relevant influence factors on takeover probability of European companies using publicly available information. Subsequently, the derived model is used to test its predictive accuracy in an out-of-sample test. In addition, the ability to generate returns through takeover prediction in the two European regions is tested, using decile portfolios. These analyses give a deeper insight into the efficiency of markets concerning takeovers and expected takeovers in the European market.

The various rational and irrational motivations for takeovers make it impossible to find a one-size-fits-all model, explaining all kinds of takeovers. Like previous studies in this line of research, the prediction model of this thesis is based on the market for corporate control. A further limitation of this type of analysis is of course the dependence on the availability of takeover data, which can be used for the derivation of the model and the subsequent tests to generate abnormal returns. Hence, data of the last financial year reporting of the takeover targets and the control sample are used in this analysis to avoid backfill bias and have a realistic prediction situation for already known information.

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[11] For this analysis, the three continental European countries with the highest takeover activity, namely France, Germany and Sweden are selected. Furthermore, Switzerland as a country of regional importance to this thesis is included.

[12] LaPorta, Lopez-de-Salanes, Shleifer and Vishny(1998) find in their study legal systems for 49 countries, that investor protection is largest for common-law countries like the United Kingdom, mediocre for German-and Scandinavian-civil-law countries and lowest for French-civil-law. This is in line with less developed capital markets and lower ownership concentration. Furthermore, Goergen & Renneboog (2004, p. 23), find significantly higher cumulative average abnormal returns to target shareholders and more efficient pricing of the announcement information in the UK and Contiental Europe..

4. Empirical Analysis

In the following section, a prediction model for takeovers in the European market is developed, testing the influence factors of takeover probabilities. Furthermore, the influence of these factors on the level of abnormal returns to the target shareholders is analyzed in a second analysis. This allows an attempt to maximize the abnormal return of an investment in predicted takeover targets, as one can optimize the results to find potential takeover targets that have a high abnormal return.

4.1 Takeover prediction

For the takeover prediction model in this section, a multivariate logistic regression model matched by industry and year is used to estimate a takeover prediction model. Based on a set of eight hypotheses, the influence factors of the takeover probability of companies are identified in the empirical analysis. The approach uses the hypotheses of Palepu (1986) as a basis and combines them with selected additional hypotheses and variables. The analysis is applied for European market sample including the United Kingdom, France, Germany, Sweden and Switzerland to be able to assess the takeover probability of European listed companies using public information.

4.1.1 Hypotheses

For the takeover prediction analysis, the six hypotheses inefficient management, firm size, growth-resource imbalance, industry disturbance, market-to-book (M/B) hypothesis and price-earnings hypothesis by Palepu (1986) are used as a basis for the hypotheses used in the logit regression model. In addition, hypotheses for leverage, liquidity and investment behavior are tested for their significance in the assessment of takeover probability. These are described below:

Hypothesis 1: Inefficient management - Firms with inefficient management have a higher probability of being taken over.

Based on the existing body of research[13], it is assumed that inefficiently managed firms have a higher probability to be taken over, as Jensen and Ruback's (1983) management competition model already states. The employed variables[14] for this hypothesis are sales growth, EBITDA margin, return on equity (ROE) and asset turnover, as they are assumed to be the most relevant for the assessment of the firm's management success.

[13] See, e.g. Palepu (1986), Ambrose & Megginson (1992), Barnes (1999), Powell (2001), Brar, Giamouridis & Liodakis (2009) and Cremers, Nair & John (2009).

[14] For a detailed description of the variables see appendix A2.

Hypothesis 2: Firm size – Smaller firms have higher probability of being taken over.

Various empirical studies[15] assume a negative relationship between firm size and takeover probability. The variables used to test this relationship are market capitalization, sales and total assets.

Hypothesis 3: Growth-financial resource mismatch – Firms with mismatching growth compared to financial resources have a higher probability of being taken over.

This hypothesis originates from Palepu (1986) and is used in other studies (see, e.g. Ambrose & Megginson, 1992; Powell, 2001). It is assumed that if the firm has either high growth and few financial resources or low growth and high financial resources, measured in a dummy variable, there is a higher chance that the firm is taken over. Similar to the study by Palepu (1986, p. 17), this dummy variable is determined based on growth, liquidity measured as cash and marketable securities to total assets as well as leverage, measured as a debt to equity ratio. The dummy variable has the value one if there is either low growth + high liquidity + low leverage or high growth + low liquidity + high leverage (Palepu, 1986, p. 17).

Hypothesis 4: Undervaluation – Firms with lower valuations have a higher probability of being taken over.

In this hypothesis, the two hypotheses of market-to-book value as well as price-earnings-ratio hypothesis by Palepu (1986) are combined, expecting a higher takeover probability for undervalued companies. As the two hypotheses already imply, M/B-ratio as well as P/E-ratio are used as variables for this hypothesis.

Hypothesis 5: Industry disturbance – Firms affected by an industry shock have a higher probability of being taken over.

Based on the industry disturbance hypothesis proposed by Gort (1969) and Mitchell and Mulherin (1996) an the industry shock in industry of a firm is assumed to have a positive influence on the takeover likelihood. The presence of an industry shock is defined in a dummy variable of a value equal of one if at least one transaction took place in the same SIC code during the previous year.

Hypothesis 6: Leverage – Firms with with higher leverage have a higher probability of being taken over.

Having been employed in several prediction models of previous empirical studies (see, e.g. Dietrich & Sorensen, 1984; Brar, Giamouridis & Liodakis, 2009; Cremers, Nair & John, 2009), this hypothesis suggests a positive relationship between takeover probability and leverage, measured as a ratio of debt to equity. Brar, Giamouridis and Liodakis (2009) argue that takeover targets are often financially distressed and have higher debt to equity ratios as a consequence.

[15] See, e.g. Dietrich & Sorensen (1984), Palepu (1986), Ambrose & Megginson (1992), Barnes (1999), Brar, Giamouridis & Liodakis (2009) and Cremers, Nair & John (2009).

Hypothesis 7: Liquidity – Firms with lower liquidity have a higher probability of being taken over.

Related to the previous hypothesis in the idea that takeover targets have lower financial power, this hypothesis is rather related to a shorter-term financial capacity. Brar, Giamouridis and Liodakis (2009) find a significantly lower liquidity, measured as cash-to-total-capital ratio, for targets compared to their peers. This empirical study of this thesis tests the liquidity hypothesis through a cash-to-total-assets ratio as well as a current ratio (current assets / current liabilities), which is a good indicator for short-term financial capacity.

Hypothesis 8: Investment behavior – Firms with higher investments have a higher probability of being taken over.

This hypothesis is suggested for this thesis based on the idea that acquirers look for targets with certain tangible or intangible assets and a competitive advantage related to this. Hence, the target firm must have a future-oriented investment behavior that could imply a stronger investment focus, measured as a ratio of capital expenditures (CAPEX) to sales.

4.1.2 Data

For the estimation of the takeover prediction model in a conditional logit regression approach, a sample of targets and of non-targets is required for the estimation sample. The data selection and description of the two samples is illustrated in the following part.

Target sample

The target data sample was selected to include relevant transactions for the UK and Continental Europe to use for the prediction model and also later for the event study in the assessment of target shareholder announcement returns. First, all completed public European takeovers[16] larger than $10m of enterprise value within industries other than financial industry[17] are retrieved from the Thomson ONE database. This raw data consist of 4,742 transactions from all European countries for announcement dates from 1985-2012. Second, a screening for data availability was done to ensure the availability of the required data for the chosen variables[18] for all transactions in the final sample. France, Germany and Sweden are chosen to be included in the Continental European sample, as they have the largest share of deals within the non-UK countries. In addition, Switzerland is included, as it is a coun-

[16] Takeovers in this context were selected as M&A transactions, which increase the ownership stake of the acquirer from less than 50% before the announcement of the transaction to more than 66.66% after the announcement of the transaction.

[17] Just as in comparable studies (see e.g. Palepu, 1986; Ambrose & Megginson, 1992; Powell, 2001; Brar, Giamouridis & Liodakis, 2009) transaction in financial industry (SIC 6xxx) were excluded from the sample due to the limited comparability of financial data to other industries.

[18] The list of used variables can be found in appendix A2.

try of regional interest to this thesis. Furthermore, as the number of transactions announced during the period from 1985 to 1995, fulfilling the data requirements is not sufficient to allow a reasonable analysis, the final sample consists of deals for the target markets of the UK, France, Germany, Sweden and Switzerland for the years 1996-2012. Hereof, the transactions from 1996-2010 (15 years) are used as an estimation sample for the prediction model and the years 2011 and 2012 are used as a hold-out sample for an out-of-sample test to determine the prediction success. After the outlier elimination[19], the final estimation sample for the prediction model consists of 856 takeovers, of which 518 are in the UK and 338 are in Continental Europe.

Table 5
Targets: Sample composition

This table shows the number and percentage of targets for the sample of 856 targets by country. The sample for 1996-2010 is used for the estimation of a takeover prediction model. The data were retrieved from Thomson ONE.

	No. of obs	*Percent*
Total	856	100%
United Kingdom	518	60.51%
France	131	15.30%
Germany	99	11.57%
Sweden	77	9.00%
Switzerland	31	3.62%

The distribution of the number of deals in the sample for the UK and for Continental Europe over time can be seen in figure 4. Despite possible distortion due to data availability, a wave pattern can be observed in the distribution of targets over time. The fifth merger wave with its peak in 1999-2000 can be clearly identified, but only a small hint of the sixth merger wave with its peak in 2007.

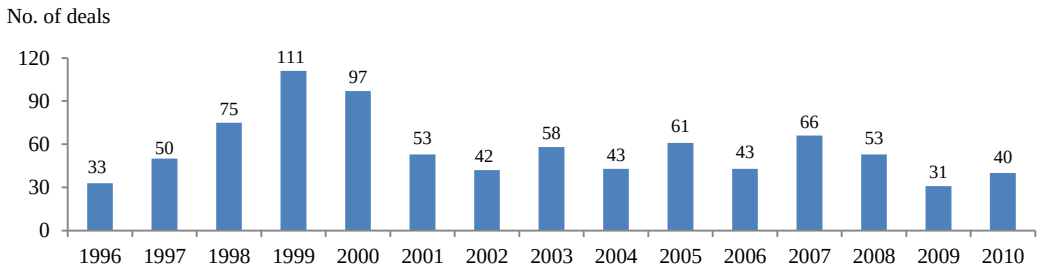


Fig 4. Target sample over time. The data were retrieved from Thomson ONE.

Descriptive statistics of the target sample are provided in table 6, giving an overview of the different variables assigned to the eight hypotheses. Due to the elimination of deals with insufficient data, all variables are available for the 856 European takeover targets from 1996-2010.

[19] The exact outlier elimination and the rationale behind the individual decisions is provided in appendix A2.

Table 6
Targets: Descriptive statistics

This table provides descriptive statistics for the eight hypotheses and their respective variables. The data were retrieved from Thomson ONE.

	No. of obs.	Mean	St. dev	Min	Max
Inefficient Management					
1-year sales growth	856	14.017%	61.994%	-71.723%	1,153.172%
2-year sales growth	856	17.494%	66.501%	-51.805%	1,546.056%
EBITDA-margin	856	10.406%	21.502%	-266.313%	86.159%
Return on Equity (ROE)	856	8.379%	59.852%	-471.420%	767.497%
Asset turnover	856	1.30995	0.84958	0.03945	8.83227
Firm size					
Sales (m)	856	1,233.53	4,506.26	5.419	88,844.85
Market capitalization (m)	856	1,405.62	5,936.91	10.16	75,955.93
Total assets (m)	856	1,358.45	5,285.45	4.185	93,707.23
Growth resource					
Dummy	856	24.299%	42.914%	0	1
Undervaluation					
P/E	856	20.778	50.614	-192.883	444.48
M/B	856	1.3056	1.394	0.005	14.044
Industry dummy					
Dummy	856	25.584%	43.659%	0	1
Leverage					
Leverage	856	0.34896	0.4972	0.00016	6.01521
Liquidity					
Cash/total assets	856	11.538%	13.260%	0.003%	85.663%
Current ratio	856	105.09%	106.48%	4.465%	1,801.416%
Investment behvaior					
CAPEX / Sales	856	7.359%	11.095%	0.063%	90.578%

Non-target sample

The sample of non-targets is needed as a control group. A comparison of target data with non-target data of companies in the same industry and year in a conditional logit regression is done in order to identify significant factors influencing the takeover probability of companies. Therefore, a list of all 4,762 active and non-active listed companies in the five studied countries (UK, France, Germany, Sweden and Switzerland) is retrieved from Thomson ONE's company screening function, including a firm identifier[20] and the industry code[21]. Subsequently, the relevant yearly data for the non-target sample were retrieved from Bloomberg for 1996-2012 including the relevant data variables for 4,732 listed companies. Excluding financial services companies and takeover targets, this leaves a list of 3,441 firms in the control sample. Outlier elimination is done the same way as for the target sample[22].

[20] SEDOL (Stock Exchange Daily Official List) code was used a firm identifier.

[21] As an industry code the four-digit standard industrial classification (SIC) code is provided to identify the specific industries.

[22] See details about outlier elimination process in appendix A2.

After dropping the observations[23] with insufficient data, 18,808 observations are left for the years 1996-2010 (estimation sample), which can be matched with the relevant targets in the prediction model estimation via conditional logit regression. As for the targets, data for 2011 and 2012 are used as a hold-out sample for the out-of-sample test. The non-target sample is more evenly distributed among the five countries than for the target sample, while the UK, France and Germany still represent the majority of the observations.

Table 7
Non-targets: Sample composition
This table shows the number of non-targets in the control sample of 18,808 observations by country. The data were retrieved from Bloomberg based on a list of listed firms from Thomson ONE.

	No. of obs	*Percent*
Total	18,808	100%
United Kingdom	6,498	34.55%
France	4,226	22.47%
Germany	4,608	24.50%
Sweden	1,733	9.21%
Switzerland	1,743	9.27%

Figure 5 reveals a clear positive relation between time and the number of observations in the sample. This could be caused both by the number of listed firms and the availability of the required data variables over time.

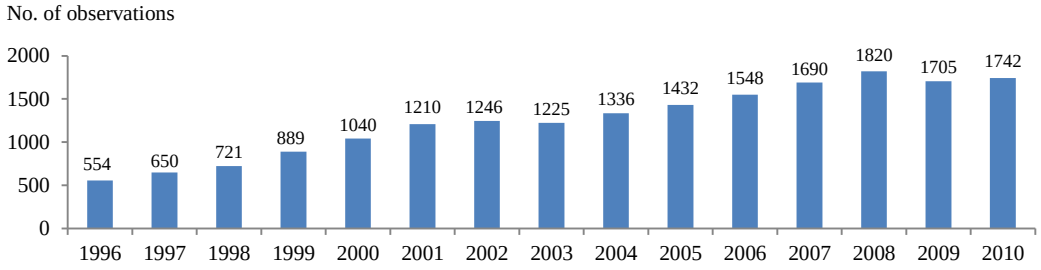


Fig 5. Non-target sample over time. The data were retrieved from Bloomberg based on a list of listed firms from ONE.

Descriptive statistics of the non-target sample are provided in terms of the number of observations, mean, standard deviation, minimum and maximum for all variables assigned to the eight hypotheses. Like for the target sample, the elimination of observations with insufficient data leads to a control sample with 18,808 observations for each variable in the estimation sample of the listed European firms from 1996-2010.

[23] This is the financial data for one specific year of one listed non-target.

Table 8
Non-targets: Descriptive statistics

This table provides descriptive statistics for the eight hypotheses and their respective variables for the non-target estimation sample. The data were retrieved from Bloomberg based on a list of listed firms from Thomson ONE.

	No. of obs.	Mean	St. dev	Min	Max
Inefficient Management					
1-year sales growth	18,808	22.331%	92.613%	-79.793%	4,857.396%
2-year sales growth	18,808	33.589%	126.727%	-76.752%	4,391.958%
EBITDA-margin	18,808	10.334%	26.712%	-1,239.20%	309.517%
Return on Equity (ROE)	18,808	7.435%	52.458%	-497.901%	967.068%
Asset turnover	18,808	1.17279	0.72699	0.03104	9.51687
Firm size					
Sales (m)	18,808	2,922.07	11,531.69	5.004	361,143
Market capitalization (m)	18,808	2,816.94	12,761.83	10.00	414,796
Total assets (m)	18,808	3,675.03	15,971.16	2.45	366,914
Growth resource					
Dummy	18,808	27.084%	44.441%	0	1
Undervaluation					
P/E	18,808	16.2864	41.641	-199.246	498.098
M/B	18,808	1.11687	1. 3295	0.0063	18.9867
Industry dummy					
Dummy	18,808	45.279%	49.778%	0	1
Leverage					
Leverage	18,808	0.32356	0.56095	0	41.1337
Liquidity					
Cash/total assets	18,808	14.116%	14.643%	0	94.201%
Current ratio	18,808	181.343%	144.308%	3.962%	1,932.611%
Investment behavior					
CAPEX / Sales	18,808	6.347%	9.441%	0	98.5172%

4.1.3 Methodology

The influence of the different variables and the test of the hypotheses for takeover prediction is done by comparing the data for target companies in a specific year and industry with comparable non-target firms, that were not taken over. As in previous empirical studies published since the mid-80s (see, e.g. Palepu, 1986), this empirical study uses a multivariate logistic regression model (logit regression model) to determine a functional relationship between the firm- and industry-variables and the takeover likelihood. Therefore, the independent variables based on the various hypotheses are regressed on the dependent variable "targetdummy"[24]. A t-test for the difference in the means of the two samples and a correlation analysis are first used to identify an optimal set of variables for the eight hypotheses to include in the conditional logit regression model. This reduces issues of multicollinearity between the variables and improves the model.

To get a first indication of differences in the mean of the two samples, a t-test is performed for all variables of the eight hypotheses. The two independent samples x_1 (non-targets with n_1=18,808) and x_2

[24] Firms that were taken over have targetdummy=1 (target) and firms not taken over targetdummy=0 (non-target).

(targets with n_2=856) are tested for a statistically significant difference in sample means. The null hypothesis is assumed as H_0: $\mu(\bar{x}_1 - \bar{x}_2)=0$ and the alternative hypothesis H_1: $\mu(\bar{x}_1 - \bar{x}_2)\neq 0$ (Weiers, 2008, p. 363). The t-statistic for the comparison of the means of the two independent samples x_1 and x_2, assuming equal σ_1 and σ_2 can be calculated as

$$t = \frac{(\bar{x}1 - \bar{x}2) - (\mu 1 - \mu 2)_0}{\sqrt{s_p^2(\frac{1}{n_1} + \frac{1}{n_2})}} \quad (2)$$

,where $s_p^2 = \frac{(n_1-1)s_1^2 + (n_2-1)s_2^2}{n_1 - n_2 - 2}$ is the pooled estimate of the common standard error and $(\mu_1 - \mu_2)_0$ is the hypothesized difference between population means (Weiers, 2008, p. 365).

Subsequently, a correlation matrix for all variables is calculated to observe the interdependence of the various variables. It is based on the combination of target and non-target samples. This analysis enables the identification of variables with low correlation to other factors and allows a certain degree of reduction in multicollinearity through the according choice of variables to include in the prediction model.

A logit regression model combines all the selected factors into one model to estimate a prediction model. It enables us to condense the probability to a value between zero and one, which would not be possible with a simple linear regression model (Agresti & Finlay, 2009, pp. 483-484). Only the log odds (logit) have a linear relationship in the form:

$$logit[\pi(x)] = log\frac{\pi(x)}{1-\pi(x)} = \alpha + \beta x \quad (3)$$

If equation (3) is transformed to directly express the probability of a firm of being a target, the basic logistic regression model is $P(y = 1) = \frac{e^{\alpha+\beta x}}{1+e^{\alpha+\beta x}}$, using one independent variable (Agresti & Finlay, 2009, p. 486; Agresti, 2002, p. 166). Hereby, maximum likelihood estimation is used for the fitting of the model by most software packages[25] as this achieves better results for binary data than the ordinary least squares (OLS) method (Agresti & Finlay, 2009, p. 485).

The model used by Palepu (1986, p. 15) is a multivariate logistic regression model in the form:

$$p(i,t) = \frac{1}{1+e^{-\beta x(i,t)}} \quad (4)$$

, where *p (I, t)* describes the probability that a firm *i* is taken over in period *t*. The *x (i, t)* represents a vector of independent firm- and industry-variables and *β* a vector of parameters that have to be estimated. For the independent variables, the data of the last financial reporting at the point of the prediction is chosen so that a problem with backfilling is avoided.

To improve the results of the analysis, a conditional logit regression model is used to analyze only the comparable pairs of target and non-target firms. Matched pairs (Y_1, Y_2), where Y_1 is a target and Y_2 is a non-target, are analyzed, while the parameters *ß* are dependent on matching data (see, e.g. Agresti, 2002, p. 414). The year of the observation of the non-target firm and industry code (SIC) has

[25] For the analysis in this thesis, the software package STATA is used.

to match the target firm's data to be considered in the analysis. One target can be matched with multiple non-target firms.

4.1.4 Empirical results

As described above, the analysis is split into three parts. First, the difference in the means of the various variables for the eight hypotheses is tested. Second, a correlation analysis points out the interdependencies between the variables. Third, the conditional logit regression is performed to estimate a prediction model for the assessment of takeover probabilities of European public companies.

The test for difference in the means of the firm- and industry-specific companies is conducted to show statistically significant differences in the means of the target and non-target sample. In this analysis the entire number of observations of the two samples is considered and no matching is done yet. The results (see table 9) show a statistically significant difference in the mean of most variables. The *inefficient management hypothesis* is confirmed with regard to one and two year compounded annual growth rate (CAGR), but shows a significantly higher asset turnover for targets, which is contrary to the expectation. For EBITDA-margin and return-on-equity (ROE) no statistically significant difference for the unmatched sample can be found. *Firm size hypothesis* is confirmed as being significantly lower for targets than for non-targets. *Growth-resource-imbalance hypothesis* is larger for non-targets, which is contrary to the expectations in Palepu (1986). Similar findings are observable for *undervaluation hypothesis* and *industry disturbance hypothesis*, where the results of the t-tests are contrary to the expectation. The three hypotheses introduced in addition to the ones proposed by Palepu (1986) are all found statistically significant in the expected way. *Leverage hypothesis* and *liquidity hypothesis* are confirmed, indicating a weaker financial situation of takeover targets compared to non-targets. Furthermore, the newly introduced *investment behavior hypothesis* is confirmed in the t-test, showing that target firms have a higher rate of investments compared to non-targets.

The correlation matrix[26] indicates interdependencies at a statistically significant level of 5% for a large share of the variable combinations, however the level of correlation between most of the variables is low. Very strong and highly significant correlations are found between the size variables sales, equity value and total assets. Hence, only one of these should be included in the logit regression model. Due to the higher and more statistically significant correlations of sales and total assets with the other variables, equity value is selected as the variable, which is included in the third part of the analysis. Furthermore, the two-year sales CAGR is included as it has lower correlations and stronger difference in the t-test. Price-earnings-ratio is selected due to its much lower interdependencies with other variables compared to market-to-book ratio. The same applies for current ratio compared to cash-to-total assets. Besides the described variables, EBITDA-margin, the growth-resource imbalance dum-

[26] The correlation matrix for all variables can is shown in appendix B2.

my, industry disturbance dummy as well as CAPEX-to-sales ratio are selected for the logit regression model. Hence, nine variables are included in the prediction model for the eight hypotheses.

Table 9
T-tests for for difference in means

This table provides two sample t-tests for the eight hypotheses and their respective variables. It tests the difference in means between non-targets and targets. The data were retrieved from Thomson ONE.

	Targets (mean)	Non-targets (mean)	t-test	p-value
Inefficient Management				
1-year sales growth	14.017%	22.331%	2.600***	0.0047
2-year sales growth	17.494%	33.589%	3.693***	0.0001
EBITDA-margin	10.406%	10.334%	-1.078	0.4690
Return on Equity (ROE)	8.379%	7.435%	-0.511	0.3046
Asset turnover	1.30995	1.17279	-5.356***	0.0000
Firm size				
Sales (m)	1,233.53	2,922.07	4.269***	0.0000
Market capitalization (m)	1,405.62	2,816.94	3.220***	0.0006
Total assets (m)	1,358.45	3,675.03	4.233***	0.0000
Growth resource				
Dummy	24.299%	27.084%	1.796**	0.0363
Undervaluation				
P/E	20.778	16.2864	-3.055***	0.0011
M/B	1.3056	1.11687	-4.053***	0.0000
Industry dummy				
Dummy	25.584%	45.279%	11.378***	0.0000
Leverage				
Leverage	0.34896	0.32356	-1.302*	0.0965
Liquidity				
Cash/total assets	11.538%	14.116%	5.058***	0.0000
Current ratio	105.09%	181.343%	15.274***	0.0000
Investment behavior				
CAPEX / Sales	7.359%	6.347%	-3.042***	0.0012

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

The prediction model is estimated using the targets and non-targets for 1996-2010 in a conditional logit regression model, while matched by year of the deal/observation and industry code (4-digit-SIC). Based on this matching, 4,741 observations are included in the regression models. In addition, the model is adjusted for a UK-dummy variable due to the large size of UK-deals in the sample. Four conditional logit regression models are provided in table 10. First, just the firm-specific hypotheses for *inefficient management, size, undervaluation* and *growth resource imbalance* based on Palepu (1986) are included. The second model adds *industry disturbance hypothesis* to this. Model 3 employs all variables including *leverage, liquidity* and *investment behavior hypotheses*. All of these three models include the adjustment for the UK-dummy variable, so a forth model excludes this factor to show the influence of it in the model.

The results of the analysis (see table 10) find statistically significant results for 2-year-sales-CAGR, EBITDA-margin, PE-ratio, industry disturbance, current ratio and the UK-dummy. The logit regression models indicate a confirmation of the *inefficient management hypothesis* and *liquidity hypothesis.*

Contrary to the expectation of the literature, PE ratios are significantly higher for targets than for non-targets and industry disturbance, meaning takeovers in the same industry during the previous year has a negative influence on the likelihood that a firm is taken over. The UK-dummy has a significantly positive influence on the takeover probability of a listed European firm, which might have other reasons than the pure geographic location, as differences in investor protection between the UK and other European countries exist (see, e.g. LaPorta et. al, 1998). The variables of the *size, growth-resource-imbalance* and *investment behavior* hypotheses are not found to have a statistically significant influence in this model. As the provided coefficients are logit coefficients, just the direction of the relation can be interpreted directly.

The comparison of the statistical significance of the various models shows that the basic firm-specific variables have rather low explanatory power, while it is dramatically increased by the *industry disturbance hypothesis* and is further increased by adding the three additional variables for the *leverage, liquidity* and *investment behavior hypothesis.* Overall, the model is very significant and the pseudo R^2 of 0.3963 indicates a high explanatory power of takeover probability through the ten selected factors.

Table 10
Conditional logit regressions for takeover prediction model

This table presents the results of conditional logit regression models for the estimation of a takeover likelihood model. Four different models are estimated. Model 1 uses the firm-specific hypotheses based on Palepu(1986) and controls for the UK-dummy. Model 2 adds the industry disturbance to the hypotheses in model 1. Model 3 adds the additional firm-specific hypotheses leverage, liquidity and investment behavior. Model 4 shows the impact of the UK-dummy adjustment in the full model (3). The takeover prediction model is estimated using a conditional logit regression matched by year of the observation and industry code. Data were retrieved from Bloomberg and Thomson ONE.

	(1)	**(2)**	**(3)**	**(4)**
No. of observarions	4,741	4,741	4,741	4,741
LR χ^2	159.84	731.51	908.60	842.00
Prob> χ^2	0.0000	0.0000	0.0000	0.0000
Pseudo R^2	0.0697	0.3191	0.3964	0.3673
Variables				
2-year-CAGR	-0.5529***	-0.6242***	-0.5548***	-0.5615***
	(-5.35)	(-5.09)	(-4.38)	(-4.60)
EBITDA-margin	-0.3124**	-0.4918***	-0.7048***	-0.6619**
	(-2.09)	(-2.89)	(-2.74)	(-2.52)
ln(EQV)	0.0133	0.0241	-0.02980	-0.0343
	(0.51)	(0.78)	(-0.90)	(-1.06)
PE-ratio	0.0028***	0.0045***	0.0042***	0.0034***
	(2.96)	(3.98)	(3.77)	(3.12)
GR-dummy	-0.1645	-0.2024	0.1643	0.1681
	(-1.49)	(-1.56)	(1.17)	(1.22)
Industry disturbance		-5.1861***	-4.8935***	-4.7633***
		(-14.81)	(-13.81)	(-13.52)
Leverage			-0.1756	-0.2964**
			(-1.33)	(-2.30)
Current ratio			-1.1925 ***	-1.2650***
			(-10.69)	(-11.28)
CAPEX/Sales			0.2000	0.0491
			(0.30)	(0.07)
UK-dummy	1.0219***	1.1283***	1.0305***	
	(9.89)	(9.16)	(7.95)	

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

4.2 Takeover returns

In a second analysis, this section examines the influence of the factors used in the takeover prediction model on the level of abnormal returns to the target shareholders in case of a takeover. This allows us to make statements about the interdependence of takeover probability and target announcement returns related to the employed prediction factors. Hence, the analysis shows how well it is possible to identify targets that have a maximal expected return as a product of a high takeover probability and a high return to target shareholders.

4.2.1 Hypotheses

The theoretical section[27] of this thesis provided a short overview of non-deal factors that were found to have an influence on the level of target shareholder returns during takeovers. Based on the literature, firm size has either a positive (see, e.g. Melicher & Nielsen, 1978; Jackson & Gart, 1999) or a negative (see, e.g. Eckbo, 2009) influence on takeover returns. Undervaluation measured in terms of market-to-book ratio can be expected to have a negative relationship (see, e.g. Walking & Edmister, 1985; Eckbo, 2009). As there is only little empirical evidence on this field, the rest of the hypotheses could only be guesstimated, which is not attempted here. The following analysis studies the influence of the variables applied in the prediction model on the cumulative abnormal return (CAR) of the targets for different event windows, which are derived in an event study.

4.2.2 Data

The same target data[28] are employed in this analysis that is already used for the takeover prediction model. In addition, the stock returns for the 250 trading days before and 50 trading days after the takeover announcement of the individual targets are used for the event study and the calculation of the CARs. This includes an estimation window of 200 days and an event window of 50 trading days before until 50 trading days after the takeover announcement. The share price data are retrieved from Bloomberg. If it is not possible to get the required data for specific targets, these are excluded from the analysis. Furthermore, the prices of the MSCI Europe Index are accessed to use them in the OLS market model of the estimation window as well as for the calculation of the abnormal returns of the event period.

4.2.3 Methodology

For this analysis, event study methodology is used to determine the abnormal returns for target shareholders during the event window around the announcement of a takeover. McWilliams and Siegel

[27] See chapter 2.3.1

[28] See chapter 4.1.2

(1997, pp. 630 - 634) state the three assumptions of event studies as efficiency of markets, that the event has to be unanticipated by the market and has to be unaffected by possibly confounding events.

The market model $E(R_{i\tau}) = \alpha_i + \beta_i R_{m\tau} + \varepsilon_{i\tau}$ gives the foundation for the calculation of the abnormal returns, as it is used to determine a functional relationship between the market return $R_{m\tau}$ and the expected return $E(r_{i\tau} \mid X_\tau)$ (MacKinlay, 1997, pp. 18-19). The market portfolio is defined as the MSCI Europe index for this event study, because it is assumed that this is a good indicator for European equity market developments. The literature on event studies itself as well as the empirical studies on takeover return use diverse ranges of estimation windows between 120 and 239 days[29]. While the length of the estimation window is not specifically defined, MacKinlay (1997, p. 15) states that it should be separated from the event window to avoid influences of pre-announcement returns. As already pointed out, Schwert (1996, p, 162) and Eckbo (2009, p. 51) find no significant run-up returns more than 2 months before the takeover announcement. Therefore, this study defines the estimation window as the 200 trading days from 250 days before the announcement until 50 days before, in order to avoid influences of run-up returns on the OLS market model used to determine the expected returns. Subsequently, the abnormal returns can be calculated as the difference between actual returns and expected returns as $AR_{i,\tau} = R_{i,\tau} - E(R_{i\tau}) = R_{i,\tau} - \alpha_i - \beta_i R_{m\tau}$. These are jointly normally distributed with conditional mean equal to zero and conditional variance of $\sigma^2(AR_{i,\tau}) = \sigma^2_{\varepsilon_{i+}} \frac{1}{L_1}[1 + \frac{(R_{m,\tau} - \mu_m)^2}{\sigma^2_m}]$ (MacKinlay, 1997, pp. 20-21; Brown & Warner, 1985, p. 7). The abnormal returns can further be summarized for a period from τ_1 to τ_2 as the $CAR_i(\tau_1,\tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i,\tau}$, which has a variance of $\sigma_i^2(\tau_1,\tau_2) = (\tau_2 - \tau_1 + 1)\sigma^2_{\varepsilon_t}$ and can , like the abnormal return, be transformed into a cumulative average abnormal return (CAAR), by taking the average over a number of firms of a certain category (MacKinlay, 1997, p. 21). Moreover, a t-test with $t = \frac{CAAR(\tau_1,\tau_2)}{\sqrt{var(CAAR(\tau_1,\tau_2))}}$ and $var\big(CAAR(\tau_1,\tau_2)\big) = \frac{1}{N^2}\sum_{i=1}^{N}\sigma_i^2(\tau_1,\tau_2)$ can be used to test the statistical difference of the abnormal return to H_0: $AR_{i,\tau} = 0$ (MacKinlay, 1997, p. 24; Brown & Warner, 1985, pp. 7-8).

After the calculation of CARs, a multiple linear regression function of the form

$$Y = ß_0 + ß_1x_1 + ß_2x_2 + \ldots + ß_kx_k + u \qquad (4)$$

is used to test the relationship between explanatory variables (x_n) and the dependent variable(Y), while other unobserved factors are included in the term "u" (Wooldridge, 2003, p. 69). The various variables used in the takeover prediction model in the previous analysis are the independent variables (x_n) used for takeover prediction on $CAR_{i,\tau}$ as the dependent variable (Y).

[29] In the event study literature, MacKinlay (1997, p. 15) proposes estimation windows of a minimum of 120 days, whereas Brown and Warner (1985, p. 6) use 239 days. Goergen & Renneboog (2004, p. 16) as an example for a European takeover return study uses a period of 195 trading days (9 months).

4.2.4 Empirical results

For this analysis, a series of event windows in the range from [-1, +1] to [-50, +50] trading days is selected to be able to show not only the returns on the announcement day itself, but also run-up returns for the up to 50 trading days before the announcement of the takeovers. Based on the availability[30] of share price data for the firms the event study was conducted for 405 UK firms and 156 Continental European firms (panel A) and for 298 UK firms and 138 Continental European firms (panel B) for the event window up to [-50, +50] trading days. The analysis shows that the overall announcement returns for the target firm shareholders are between +11.71% and 24.91% for event windows between [-1, 0] and [-50, +50] trading days around the announcement day. The CAARs for the various event windows are all statistically significant at the 1% level.

Table 11
Cumulative average abnormal returns for various event windows

The table contains the cumulative average abnormal returns for the the larger sample of 561 observations (panel A) up to [-20, +20] trading days around the takeover announcement and for up to [-50, +50] trading days around the announcement date for smaller sub-sample of 436 observations (panel B), which overlapps in data with the panel A. The data for both samples were retrieved from Bloomberg using the transactions of the analysis for the takeover prediction model. To identify possible differences between the United Kingdom(UK) and Continental Europe(CE), the returns are shown for the overall sample as well as separate calculations for the two regions.

Event window	All CAAR (%)	All t-value	UK CAAR (%)	UK t-value	CE CAAR (%)	CE t-value
Panel A						
[-20, -1]	+8.28%	13.04***	+9.35%	12.15***	+5.50%	5.10***
[-1, 0]	+12.02%	23.29***	+12.90%	21.31***	+9.74%	10.06***
[-1, +1]	+13.74%	25.31***	+14.66%	24.04***	+11.34%	10.10***
[-2, +2]	+14.56%	25.66***	+15.57%	24.18***	+11.93%	10.40***
[-5, +5]	+16.48%	24.81***	+17.73%	23.47***	+13.23%	9.93***
[-10, +10]	+17.77%	22.39***	+19.30%	20.82***	+13.82%	9.25***
[-20, +20]	+20.50%	20.85***	+22.64%	19.87***	+14.96%	8.00***
Observations	561		405		156	
Panel B						
[-50, -1]	+11.71%	10.49***	+14.25%	10.27***	+6.22%	3.50***
[-20, -1]	+8.51%	11.85***	+10.19%	11.21***	+4.89%	4.53***
[-1, 0]	+11.64%	20.16***	+12.96%	18.21***	+8.78%%	9.33***
[-1, +1]	+13.49%	21.93***	+14.82%	20.77***	+10.62%	9.23***
[-2, +2]	+14.52%	22.47***	+15.99%	21.23***	+11.33%	9.50***
[-5, +5]	+16.47%	21.73***	+18.21%	20.76***	+12.72%	8.97***
[-10, +10]	+18.04 %	19.53***	+20.14%	18.19***	+13.50%	8.37***
[-20, +20]	+20.73%	18.19***	+23.92%	17.37***	+13.85%	7.26***
[-50, +50]	+24.91%	14.94***	+29.79%	14.86***	+14.37%	5.11***
Observations	436		298		138	

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

[30] The share price data from Bloomberg for especially the oldest transactions in the sample were not always available for the given sample, as delisted and private firms have limited coverage in Bloomberg. Furthermore, the data availability is dependent on the time between announcement and discontinuance of public trading.

One can observe that a large share of the returns is already generated as a run-up return, in line with Schwert (1996). The returns for the event windows [-20, -1] and [-50, -1] are +8.28% and +11.71%, respectively for the overall sample of panel B. However, run-up returns for the UK are more than twice the return of Continental Europe. This is also evident in the graphical presentation of the development of cumulative average abnormal returns for the two panels, shown in figures 6 and 7 below. The higher level of run-up-returns could be caused by higher levels of insider trading and rumors (see, e.g. Schwert, 1996, pp. 162-163), but must also be seen in relation to the eventual level of cumulative abnormal returns. Other than that, the pricing of the takeover announcement can be regarded as fairly efficient. The marginal correction of the CAAR in the [+1, +20] period for Continental Europe compared to the rather stable development for the UK sample could be caused by the size difference of the samples.

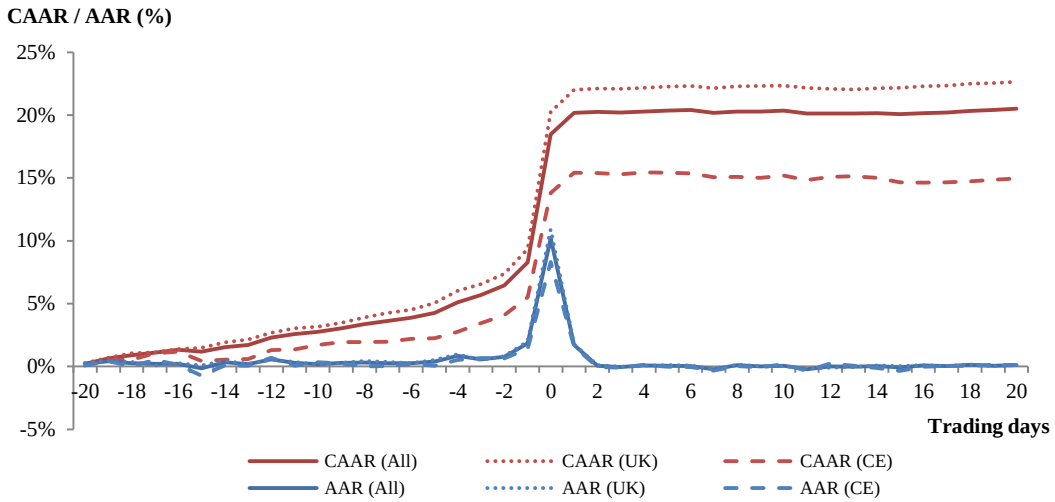


Fig 6. **Cumulative average abnormal returns for [-20, +20] event window (N=561).** Abnormal returns are calculated using a market model approach for an estimation window of 200 trading days until 50 days before the deal announcement. Stock price data were retrieved from Bloomberg.

In line with the studies by Schwert (1996) and Eckbo (2009), run-up returns are not observable more than two months (c. 42 trading days) before the announcement of a takeover. Around six weeks before the announcement of the takeover positive CAARs can be identified in the chart of figure 7. Nevertheless, the difference of just 3.20% between the [-20, -1] and [-50, -1] CAARs indicate that the returns generated until more than one month before the announcement is relatively small. More so for Continental Europe than for the UK, where 4.06% CAARs are generated compared to a mere 1.33% in Continental Europe.

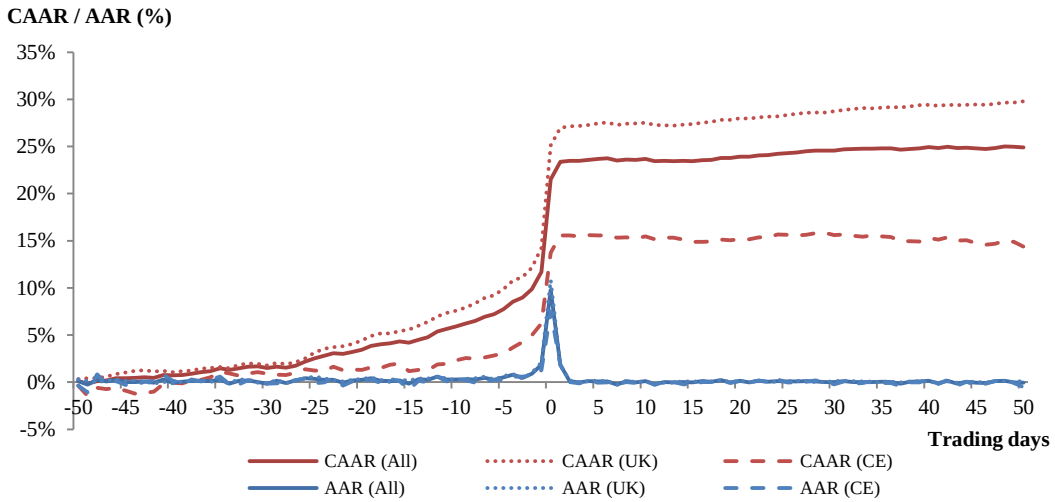


Fig 7. Cumulative average abnormal returns for [-50, +50] event window (N=436). Abnormal returns are calculated using a market model approach for an estimation window of 200 trading days until 50 days before the deal announcement. Stock price data were retrieved from Bloomberg.

Further insights about the composition of the development of CAARs for the different countries in the Continental European sample are given through a graphical illustration of the CAAR development for the UK, France, Germany, Sweden and Switzerland[31]. If the CAARs over time of the event window are compared, despite the differences in sample sizes relative to the UK sample, one can observe that especially in Germany and France the CAARs are considerably lower than for the UK, Sweden and Switzerland. The former also show rather inefficient developments, indicating an overshooting and later correction of the share prices especially for Germany.

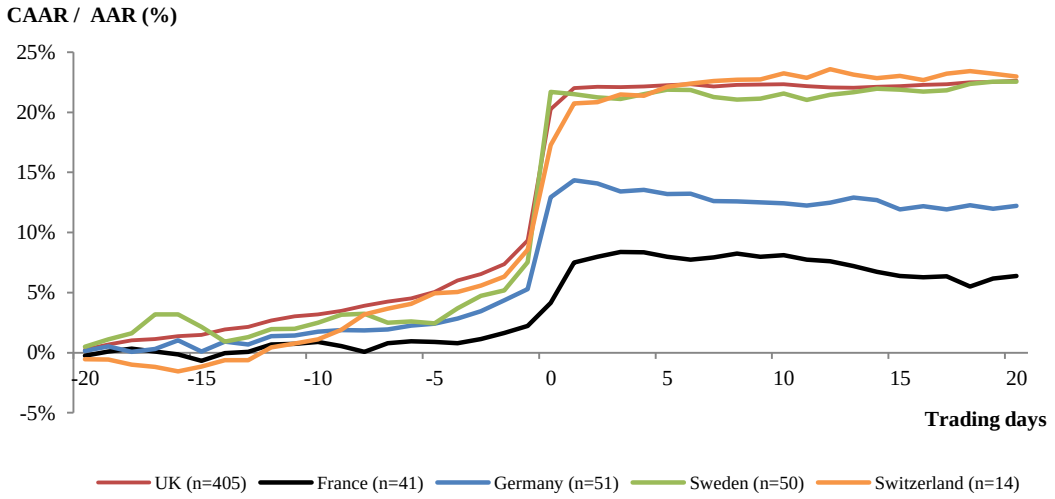


Fig 8. Cumulative average abnormal returns for [-20, +20] event window (N=561) by country. Abnormal returns are calculated using a market model approach for an estimation window of 200 trading days until 50 days before the deal announcement. Stock price data were retrieved from Bloomberg.

[31] Switzerland is included in the graphical illustration of figures 8 and 9, however due to the size of the sample (n=14), the significance of the results has to be regarded with caution if compared to e.g. the UK sample.

This observation is even stronger, if the longer event window of [-50, +50] trading days around the announcement day is regarded. Furthermore, differences in run-up returns between the countries are much more clear, as the UK generates run-up returns of 14.25% in the [-50, -1] period compared to 4.74% in France or 3.21% in Sweden.

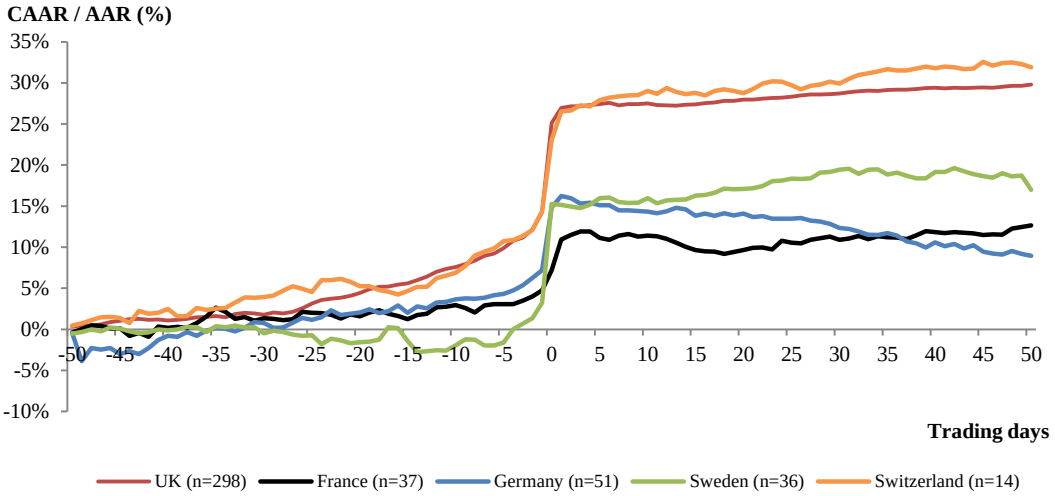


Fig 9. Cumulative average abnormal returns for [-50, +50] event window (N=436) by country. Abnormal returns are calculated using a market model approach for an estimation window of 200 trading days until 50 days before the deal announcement. Stock price data were retrieved from Bloomberg.

To test the influence of the variables used for the prediction model, an OLS-regression is run for the three main models of the prediction from chapter 4.1.4. Cumulative abnormal returns for event windows of [-50, +50] and [-20, +20] trading days around the announcement are used as dependent variables for each of the three models. The six regression models are given in table 12.

The regressions find EBITDA-margin, PE-ratios and the UK-dummy as statistically significant factors on CAR. The returns to target shareholders decrease with EBITDA-margin, increase with PE-ratio and increase substantially for UK targets. However, the UK factor is likely to be influenced by deal-specific variables such as difference in the methods of payment[32] or by differences in the CARs of different industries, which is not part of this analysis. The industry disturbance dummy variable is only statistically significant for shorter event windows of [-20, +20] trading days around the announcement day, indicating a lower return for targets in industries, which had deals the year before. The regressions for shorter event windows of [-10, +10] and [-5, +5][33] trading days give similar results with regard to EBITDA margin, PE ratios and the UK dummy. In addition, current ratio has a significantly positive relation with CAR for the shorter event windows. Industry disturbance has no significant influence for the shorter event windows.

[32] Huang & Walking (1989, pp. 342-344) find significantly higher returns to target shareholders for cash-offers than stock-offers. Hence, a larger share in cash-offers for the UK, could contribute to the positive difference of CARs for UK-targets compared to Continental European targets.

[33] The regression outputs can be found in appendix C.

Table 12
Multivariate linear regression results for cumulative abnormal returns

This table presents the results of a multivariate linear regression of the factors used for the prediction model in three different models. These factors are regressed on the cumulative abnormal return (CAR) for a [-50, +50] trading day event window (models 1-3) and on CAR for a [-20, +20] trading day event window (models 4-6). Share prices for calculation of abnormal returns using a market model were retrieved from Bloomberg. Data for all other variables are retrived from Thomson ONE as explained for the target sample in chapter 4.1.2.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
No. of observarions	436	436	436	561	561	561
F-Value	4.70***	4.30***	3.21***	4.64***	4.75***	3.55***
R^2	0.0616	0.0657	0.0616	0.0479	0.0567	0.0606
Adj. R^2	0.0485	0.0504	0.0485	0.0376	0.0447	0.0435
Variables						
Constant	0.1470**	0.1537**	0.1537**	0.1445***	0.1526***	0.1355***
	(2.18)	(2.27)	(1.86)	(3.55)	(3.75)	(2.74)
2-year-CAGR	-0.0911	-0.0078	-0.0016	-0.2967	-0.2806	-0.0244
	(-0.18)	(-0.15)	(-0.03)	(-1.27)	(-1.21)	(-1.04)
EBITDA-margin	-0.1922**	-0.1949**	-0.1748**	-0.1712***	-0.1728***	-0.1572***
	(-2.33)	(-2.36)	(-2.03)	(-3.20)	(-3.24)	(-2.85)
ln(EQV)	-0.0008	-0.0002	0.0018	0.0018	0.0020	0.0032
	(-0.08)	(-0.02)	(0.18)	(0.29)	(0.32)	(0.52)
PE-ratio	0.0007*	0.0008*	0.0007*	0.0004*	0.0005**	0.0005**
	(1.87)	(1.92)	(1.90)	(1.86)	(1.98)	(1.94)
GR-dummy	0.0065	0.0093	0.0056	0.0106	0.0151	0.0121
	(0.16)	(0.23)	(0.13)	(0.45)	(0.64)	(0.51)
Industry disturbance		-0.0519	-0.0525		-0.0498**	-0.0488**
		(-1.36)	(-1.37)		(-2.27)	(-2.22)
Leverage			-0.0360			0.0036
			(-0.99)			(0.15)
Current ratio			0.0070			0.0131
			(0.23)			(0.75)
CAPEX/Sales			-0.0937			-0.0972
			(-0.65)			(-1.08)
UK-dummy	0.1682***	0.1703***	0.1693***	0.0909***	0.0944***	0.0962***
	(4.70)	(4.76)	(4.69)	(4.08)	(4.25)	(4.30)

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

It is interesting to observe that the direction of the influence of the significant factors is the same as in the results of the logit regressions for the prediction model. This indicates a positive relationship of CAR and takeover probability with regard to these factors, which is also confirmed by a correlation analysis of the two factors (see table 13). Hence, there are no contrary factor influences that lower the expected return, as a product of takeover probability and expected returns to the target shareholders.

Table 13
Correlation analysis of estimation sample takeover probabilities and CARs

This table illustrates the correlation between the takeover probability of the targets in the estimation sample with the cumulative abnormal returns of the event study for various event windows.

	[-50, -1]	**[-20, -1]**	**[-50, +50]**	**[-20, +20]**	**[-10, +10]**	**[-5, +5]**
Takeover probability (p-value)	0.0632 (0.1182)	0.0933** (0.0209)	0.0983** (0.0403)	0.1113*** (0.0083)	0.0212 (0.6159)	-0.0057 (0.8923)

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

4.3 Interim conclusion

This chapter analyzed the influence of firm- and industry-specific factors on takeover probability and abnormal returns to target shareholders in the European market. The estimation sample of 856 targets and 18,808 observations of non-targets for the years 1996-2010 gives a foundation for the study.

In a first analysis, a prediction model was estimated using a set of up to ten variables, which were selected based on testing the difference in the means of target and non-target samples and a correlation analysis. The conditional logit regression model, matched by year of the observation and industry code identifies six statistically significant factors in model 3 at an R^2 of 0.3964. The proposed hypotheses for *inefficient management*, measured in terms of the 2-year-sales-CAGR and EBITDA margin, as well as for *liquidity*, measured with the current ratio, are confirmed. This implies that target firms have weaker performance and lower liquidity than non-targets before they are taken over. For the two hypotheses *undervaluation*, measured with the P/E-ratio, and *industry disturbance*, which is measured with a dummy variable indicating deals in the same industry during the previous year, give significant results that are contrary to the theoretical and empirical expectations. The results suggest a lower takeover probability for firms, which are subject to an industry disturbance. This might suggest that due to a short length in industry disturbances, the takeover probability of firms in a "shocked" industry already decreases for the following year. Furthermore, a positive relation between P/E-ratios and takeover probability is found in the model. The UK-dummy, which was introduced to control for the large share of UK-targets in the sample, is also found to have a statistically significant influence on takeover probability.

The second part of this chapter analyzed the influence of the employed factors from the logit regression models of the first analysis on cumulative abnormal returns (CARs) for takeover target shareholders. These returns are determined for the deals of the target sample in an event study for various event windows and split up for different regions. Statistically significant cumulative abnormal returns between +11.71% and 24.91% (see table 11) are found for event windows between [-1, 0] and [-50, +50] trading days around the announcement day, which is in line with the announcement return literature[34]. A split by region identifies considerably higher returns for targets in the United Kingdom than Continental Europe. The subsequent multivariate linear regression analyzes the factors of the first three logit models for [-50, +50] and [-20, +20] CARs and finds a significantly negative relation between EBITDA-margin and CARs and a significantly positive relation between PE-ratios and CARs. Furthermore a negative influence of an industry disturbance can be found for the [-20, +20] event window.

The analyses of non-deal-specific factors on CARs find influences in line with the direction of the influences on takeover probability. This is also confirmed in a correlation analysis between takeover probability and CARs for various event windows, finding a positive relation. Therefore, the maximiza-

[34] See chapter 2.3.1.

tion of estimated takeover probabilities is also in line with a maximization of targets shareholder returns with regard to non-deal-characteristics. Even though the correlation is not very high, this could be an indication for the inability of the market to price takeover probabilities more than a month before the announcement of a takeover. In theory, it could be assumed that the market should have priced in the higher takeover probability, leading to a negative relation between takeover probability and cumulative abnormal returns in the different event windows. The significant relationship of especially the [-20,-1] and [-20, +20] CARs compared to the [-5, +5] CARs could however be a sign that higher takeover probability leads to price adjustments in the period of four to two weeks before the announcement.

The hypothesis that a positive return can be realized based on the assessment of takeover probabilities will be tested in chapter 5. An out-of-sample test reveals the predictive power of the model. Furthermore, abnormal returns can be determined for portfolios based on takeover probability to draw reasonable conclusions about the possible success of investment strategies based on takeover prediction.

5. Prediction Tests and Portfolio Abnormal Returns

Based on the analyses conducted in chapter 4, the estimated prediction model is now tested for its predictive power. This is done through an out-of-sample test based on the hold-out sample for 2011 and 2012 to avoid biases that could occur, if the sample for the prediction accuracy test is the same that was used for the estimation of the model parameters (see Palpepu, 1986, p. 26). The predictive power of the model is assessed with a classification of the hold-out sample into potential targets and non-targets based on cutoff probabilities derived from the probabilities of the estimation sample. A classification of the hold-out sample into deciles by takeover probability allows the comparison of portfolio returns for different levels of takeover probabilities.

5.1 Predictive power of the model

In this part of the analysis, the logit regression model including all ten variables for the determination of takeover probabilities in chapter 4.1., is applied to the out-of sample data for the years 2011 and 2012. The goal is to assess the takeover probabilities of the listed firms in the five markets and test the predictive power of the model through the classification of the firm observations into expected targets and non-targets.

5.1.1 Data

The hold-out sample of listed companies for the years 2011 and 2012 in the UK and Continental Europe are used for the out-of-sample test of deriving the takeover probabilities of the various companies. This sample[35] consists of 3,470 firm observations (1,265 for the UK, 2,205 for Continental Europe), after applying the same elimination procedure that was used for the estimation sample. In addition, 18 observations were eliminated, as their stock returns, which are needed for the following takeover portfolio return derivation, were not available. The sample composition in table 13 shows that 2.02% of the firm observations for 2011 and 2012 are targets. In 2011, 2.77% of the firms or 49 firms were taken over and in 2012 1.24% of the firms or 21 firms were taken over. Furthermore, the holdout sample shows that there is a larger share of takeovers compared to the overall listed firms in the UK (2.53%) compared to the list of Continental European companies (1.75%). While the sample for France shows a similar share of takeovers of the market constituents as the UK, the percentage of deals for Germany, Sweden and Switzerland is much lower.

[35] Descriptive statistics for the hold-out sample can be found in appendix D2.

Table 14
Hold-out sample: Sample composition

This table shows the number of all observations, of targets and of non-targets in the hold-out sample for the out of sample test by country, region and year. Furthermore, the percentages of targets and non-targets in each of these categories is provided. The data were retrieved from Bloomberg based on a list of publicly listed firms from Thomson ONE.

	Total		**Targets**		**Non-targets**	
	No. of obs	*%*	*No. of obs*	*% of total*	*No. of obs*	*% of total*
Total	3,488	100%	70	2.02%	3,418	97.98%
United Kingdom	1,265	36.46%	32	2.53%	1,233	97.47%
France	744	21.44%	19	2.55%	725	97.45%
Germany	822	23.69%	10	1.22%	812	98.78%
Sweden	353	10.17%	5	1.42%	348	98.58%
Switzerland	286	8.24%	4	1.40%	282	98.60%
United Kingdom	1,265	36.46%	32	2.53%	1,233	97.47%
Continental Europe	2,295	63.54%	38	1.72%	2,167	98.28%
2011	1,772	52.12%	49	2.77%	1,723	97.23%
2012	1,698	49.03%	21	1.24%	1,677	98.76%

5.1.2 Methodology

The takeover probabilities of the listed firms for 2011 and 2012 are calculated based on the takeover prediction models in chapter 4.1. Based on the approach by Palepu (1986) the logit regression parameters (ß) derived for the different variables (x) in the prediction model are integrated into the equation $(i,t) = \frac{1}{1+e^{-\beta x(i,t)}}$. The $p\ (i, t)$ then defines the probability that a company i is taken over in period t.

5.1.3 Results

The application of the prediction model using the methodology described above enables the calculation of the takeover probabilities for the 3,470 firm observations in the hold-out sample. These takeover probabilities are the basis for the assessment of the predictive power of the model as the data in the out-of-sample test are not included in the estimation of the prediction model. The resulting takeover probabilities average 23.07% for the targets and 10.87% for non-targets. This gives a first indication that the derived probabilities could be helpful in identifying future takeover targets. Furthermore, figure 10 shows the probability density function of the targets and non-targets in the sample. It reveals a clear difference in takeover probabilities for the future targets in the sample compared to non-targets, starting at a takeover probability of close to 20%.

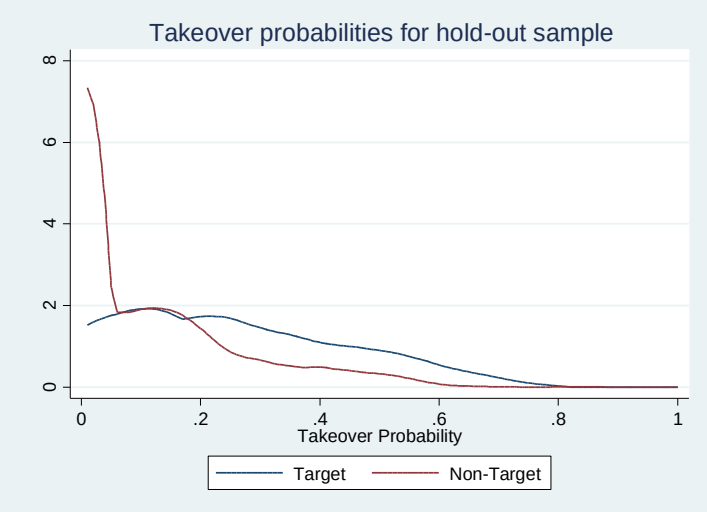


Fig 10. Comparison of probability density functions for targets and non-targets. Data are based on the determined takeover probabilities of the 3,470 firm observations in the hold-out-sample for 2011 and 2012. Source: Own graphic, generated using STATA.

The ranking of the 3,470 firm observations by takeover probability and the subsequent fragmentation into deciles gives further insight into the predictive power of the model. Compared to the overall share of 2.02% of target firms in the sample, the decile with the highest takeover probability contains almost three times as many targets and the ninth decile more than twice as many targets as the overall sample (see table 15). The same fragmentation for different sub-samples[36] for the two different years and regions shows similar trends. The share of targets in the 10th decile is up to 10.43% for e.g. the Continental European sample in 2011, while the overall share is 2.88%. The sub-sample for the UK in 2012 shows 9.38% deals in the 10% of the observations with the highest takeover probability compared to an overall share of 2.5%. Furthermore, 28.6% of the actual targets are grouped in the highest decile and 50% in the highest quintile of the takeover probabilities. Again, this indicates at least some degree of predictive power of the model in identifying future takeover targets.

Table 15
Prediction performance analysis

This table provides the number and percentage of targets and non-targets in probability ranked deciles of the hold-out sample, with the lowest probability in the 1st decile and the highest in the 10th. The probabilities were derived by applying prediction model 3, consisting of eight hypotheses and ten variables, to the hold-out sample.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Total**
Non-targets	344	345	346	341	340	347	339	339	332	327	3,400
	99.14%	99.42%	99.71%	93.27%	97.98%	100%	97.69%	97.69%	95.68%	94.24%	97.98%
Targets	3	2	1	6	7	0	8	8	15	20	70
	0.86%	0.58%	0.29%	1.73%	2.02%	0%	2.31%	2.31%%	4.32%	5.76%	2.02%
Total	347	347	347	347	347	347	347	347	347	347	3,470

[36] These listings can be found in appendix D4.

Previous empirical studies based on the methodological suggestions of Palepu (1986, pp. 11-14) use a classification test to assess the predictive accuracy of the model. Hereby, the firms are classified into expected targets and expected non-targets, depending on their takeover probability compared to a cutoff probability. This cutoff probability is determined as the intersection of the probability distributions for targets and non-targets (Palepu, 1986, pp. 11-14; 26). Applying this method based on the estimation sample of 19,664 observations, results in a cutoff-probability of 18%[37]. Hence, all observations of the holdout-sample are classified as an expected target if their takeover probability is above this cutoff. Table 16 shows the application of this method to the hold-out sample and several subsamples for the different years and regions. Using an 18% cutoff probability, the model predicts 54.29% of the targets and 75.97% of the non-targets correctly. Further tests for regional subsamples of the UK and Continental Europe find tremendous differences in cutoff probabilities. While, the UK sample consisting of 7,016 firm observations (518 targets and 6,498 non-targets) in the estimation sample, gives a cutoff probability of 31%, the sub-sample for Continental Europe (338 targets and 12,310 non-targets) has a cutoff probability of 14.7%. Due to these differences, an alternative test for the adapted regionally specific cutoff probabilities is provided in the models marked as "b". This adaption to regional differences results in a tremendous reduction in type-II-errors for the UK sample, where a non-target is mistakenly classified as a target. The consequential increase in type-I-errors, where a target is mistakenly classified as a non-target, is low in comparison. Of course there is always a tradeoff between the two errors if the cutoff probability is altered. In the empirical study of Palepu (1986, p. 27) for example a cutoff probability of 11.2%, which leads to a rather low type-I-error of just 20%, but a type-II-error of 55.3%.

Overall, the results of the tests for prediction accuracy show that the estimated takeover prediction model based on eight hypotheses gives a fairly good indication of a firm's likelihood of becoming a takeover target. However, the model is far from being perfect. Just like previous takeover prediction studies, it is not possible to derive a prediction model that accurately predicts all future takeover targets. This would only be possible, if the motivations and strategies for the takeovers would all be aligned and rationality in all acquisition and market decisions could be assumed.

[37] A graphical illustration of the probability density functions and the cutoff is given in appendix B4.

Table 16
Prediction accuracy test

This table shows the predictive accuracy of the takeover prediction model (model 3) in an out-of-sample test to a sample of 3,470 firm observations from 2011-2012. The cutoff probability is determined as the intersection between the probability density function of the targets and the non-targets in the estimation sample. It is determined separately for the entire sample (p=0.18), for the UK (p=0.31) and for Continental Europe (p=0.147), while the b-models give the region specific prediction accuracy.

No.	Sample	% Correct	Predicted targets	Actual targets	Targets Correct (%)	Type I error (%)	Predicted non-targets	Actual non-targets	Non-targets correct (%)	Type II error (%)
1	Entire sample (n=3,470)	75.53%	38	70	54.29%	45.71%	2,583	3,400	75.97%	24.03%
2	Entire sample (2011) (n=1,723))	73.19%	24	49	48.98%	51.02%	1,273	1,723	73.88%	26.12%
3	Entire sample (2012) (n=3,470)	77.97%	14	21	66.67%	33.33%	1,310	1,677	78.12%	21.88%
4	UK sample (2011) (n=3,470)	52.96%	11	16	68.75%	31.25%	320	609	52.55%	47.45%
4b		68.96%	9	16	56.25%	43.75%	422	609	69.29%	30.71%
5	UK sample (2012) (n=3,470)	59.22%	12	16	75.00%	25.00%	367	624	58.81%	41.19%
5b		75.00%	10	16	62.50%	37.50%	470	624	75.32%	24.68%
6	CE sample (2011) (n=3,470)	84.22%	13	33	39.39%	60.61%	953	1,114	85.55%	14.45%
6b		76.55%	18	33	54.55%	45.51%	860	1,114	77.20%	22.80%
7	CE sample (2011) (n=3,470)	89.32%	2	5	40.00%	60.00%	943	1,053	89.55%	10.45%
7b		82.14%	3	5	60.00%	40.00%	866	1,053	82.24%	17.76%

5.2 Portfolio abnormal returns and investment strategies

After assessing the prediction accuracy of the model through decile portfolios and the classification system using cutoff probabilities, it is now tested if a positive market return can be generated through the assessment of takeover probabilities. The returns were calculated for the specific year based on stock prices from Bloomberg. For takeover targets the last available stock price of the year was used, as some were delisted before the end of the year. The hold-out sample shows average returns of 38.90% for the 70 takeover targets and -0.91% for the 3,400 non-targets for the years 2011-2012. Hence, theoretically it should be possible to generate a positive return if enough targets are included in the portfolio.

Table 16 shows the returns for the decile portfolios for 2011 and 2012. For 2011, the decile with the highest takeover probability underperforms the MSCI Europe index, which is chosen as a relevant comparison for a European firm portfolio. Furthermore, the portfolio also underperforms the decile with the lowest takeover probability for 2011. For 2012, an outperformance of 7.32% over the market index and of 7.44% compared to the portfolio with the lowest takeover probability can be generated. However, both samples show high returns for the 4th and 5th decile portfolio. The high takeover probability portfolios for the UK show an underperformance of 0.08% for 2011 and an outperformance of 2,80% in 2012 compared to the respective low takeover probability portfolio. For Continental Europe this difference is at 1.55% underperformance in 2011 and 8.29% underperformance in 2012.

Table 17
Investment returns for out-of-sample test (2011-2012)

This table shows the returns of ten equally weighted portfolios, ranked from lowest takeover probability in the 1st to highest in the 10th portfolio. Returns are calculated for the years 2011 (n=1,772) and 2012(n=1,698), based on stock price data from Bloomberg. The market adjusted returns are calculated as the difference to the MSCI Europe Index, which had returns of -12.64% and 11.867% for 2011 and 2012, respectively.

	2011			2012		
Deciles	**Actual Targets**	**Return**	**Market adj. return**	**Actual Targets**	**Return**	**Market adj. return**
1	3	-14.46%	-1.82%	0	11.55%	-0.12%
2	2	-12.34%	0.30%	0	16.02%	4.35%
3	2	-16.16%	-3.52%	0	12.11%	0.44%
4	4	-6.85%	5.79%	2	14.31%	2.64%
5	2	-9.96%	2.68%	4	19.17%	7.50%
6	1	-15.13%	-2.49%	0	10.91%	-0.76%
7	8	-15.23%	-2.59%	0	7.68%	-3.99%
8	4	-7.50%	5.14%	1	8.65%	-3.02%
9	14	-11.07%	1.57%	4	11.65%	-0.02%
10	9	-18.95%	-6.31%	10	18.99%	7.32%
Total	49	-12.77%	-0.13%	21	13.11%	1.44%

A graphical illustration of the relationship between takeover probability and stock returns is given in figure 11. A negative overall relationship between returns and takeover probability with heteroscedastic tendency can be observed for the hold-out sample.

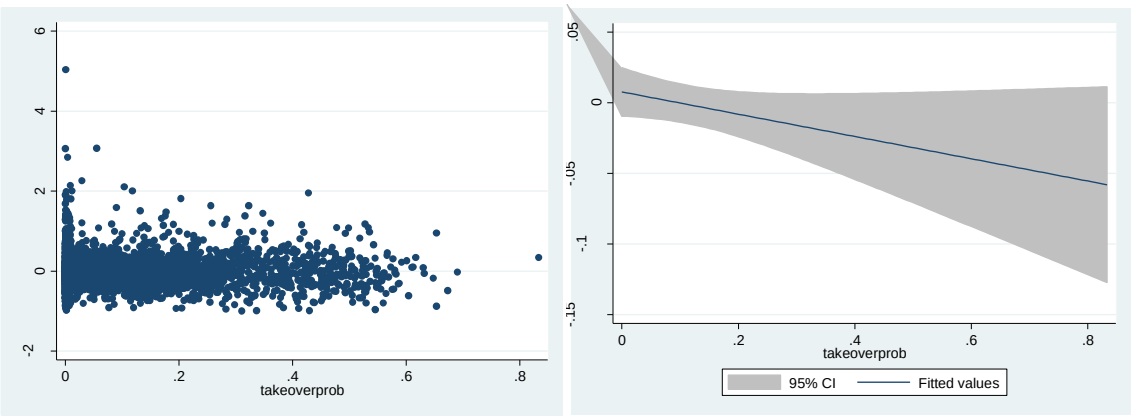


Fig 11. Relationship of return and takeover probability in the hold-out sample. A scatter plot and trend line with 95% confidence intervall of yearly returns versus takeover probability of the firm observations in the hold-out sample of 3,470 firm observations is shown for 2011-2012. Return data are calculated based on stock data from Bloomberg.
Source: Own graphics, generated using STATA.

A clear statement about the return generating potential of a takeover probability ranked portfolios cannot be made for just the two years of observations. Due to the low share of targets in the portfolios, the returns generated from takeovers are diluted by the non-targets' returns. Furthermore, the number of transactions in these two years was rather low, especially for 2012. Therefore the same analysis is done for the large estimation sample, containing 19,535 observations over a 15-year time frame (1996-2010). Contrary to the findings for 2011-2012, a clear positive relationship can be found for the overall period containing all observations (see figure 12), which might however be slightly biased in assessment of takeover probabilities as this sample is used for the estimation of the prediction model.

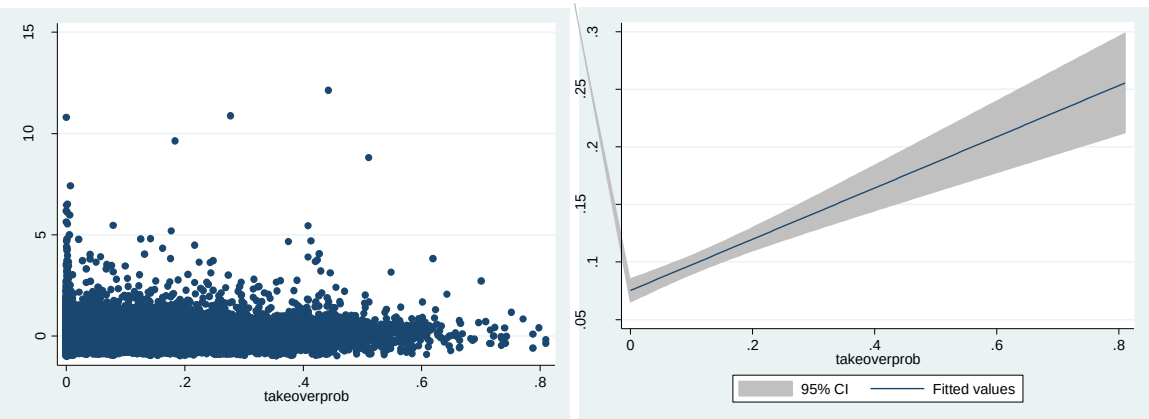


Fig 12. Relationship of return and takeover probability in the estimation sample. A scatter plot and trend line with 95% confidence intervall of yearly returns versus takeover probability of the firm observations in the hold-out sample of 19,535 firm observations is shown for 1996-2010. Return data are calculated based on stock data from Bloomberg.
Source: Own graphics, generated using STATA.

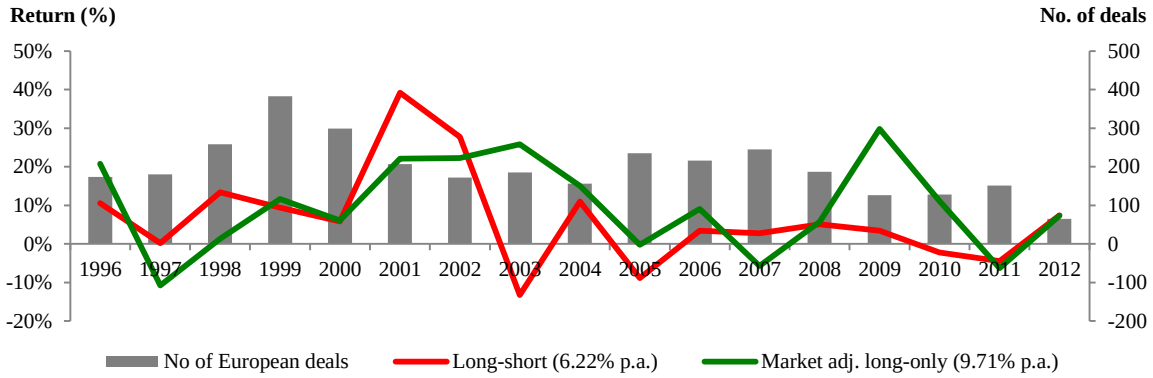
The clear positive relationship for the estimation sample and the differences for the 2011 and 2012 returns indicate that an analysis of the takeover portfolios for each year may give a clear answer to the question if and when positive returns can be generated through takeover prediction. Therefore, market-adjusted returns of the long-only portfolio and a long-short portfolio with a long position in the high takeover probability portfolio and a short position in the low takeover probability portfolio are calculated over the 17-year period from 1996-2012. This analysis is performed for the entire European portfolio as well as for separate sub-samples of the UK and Continental Europe (see figure 13). Hence, a comparison of the returns for high takeover probability firms can be made between the two markets of the UK and Continental Europe. The analysis shows that, except for a few years, a positive market-adjusted return can be generated with a long-only portfolio. A market-adjusted[38] compounded annual return of 9.71% can be generated through a long-only portfolio over the 17-year period. Over the same period, the long-short portfolio as a difference between the high and low takeover probability portfolio for each year generates a compounded annual return of 6.22%. Overall, the long-only returns tend to be higher during phases of lower M&A activity. For the long-short portfolio, no specific pattern can be identified.

The comparison of the returns for the UK and Continental Europe reveal a tremendous difference in the potential to generate returns, by trading based on the takeover probability. The long-only portfolio for high takeover probabilities generates a return that is more than three times higher in the UK than in Continental Europe, even if both returns are adjusted with the MSCI Europe (11.27% vs. 3.12%). The compounded annual return for the long-short portfolio in the UK is much lower compared to the long-only portfolio, generating 2.84% over the 17-year period. However, if compared to the same return for the Continental European sample, the potential to generate returns is more than five times higher. Overall, the volatility of the returns over the 1996-2012 time frame is much higher for the Continental European sample.

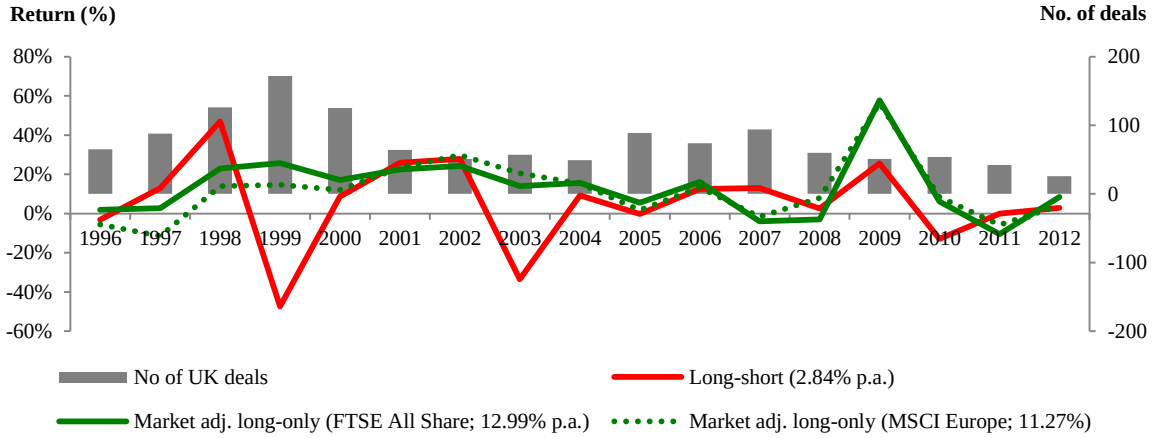
Overall, the results for the European and UK markets are in line with findings in the recent empirical literature (see, e.g. Powell, 2004; Cremers, Nair & John 2009; Brar, Giamouridis & Liodakis 2009). As in these studies, it could also be argued here that the returns may be caused by a combination of factors that may happen to generate positive abnormal returns (see, e.g. Brar, Giamouridis & Liodakis 2009). It is also possible that factors like e.g. size have a small influence here, even though ln(eqv) as the size factor was not found to be as significant and has a negative coefficient in the model for the calculation of takeover probabilities. However, the relatively good prediction accuracy of the model shows that the chance of identifying takeover targets is clearly better than by chance.

[38] The MSCI Europe Index was selected as a comparable European market index for the European sample and the Continental European sample. For the UK-sample, the FTSE All Share Index was selected in addition to show the performance relative to this regionally comparable index.

Europe



United Kingdom



Continental Europe

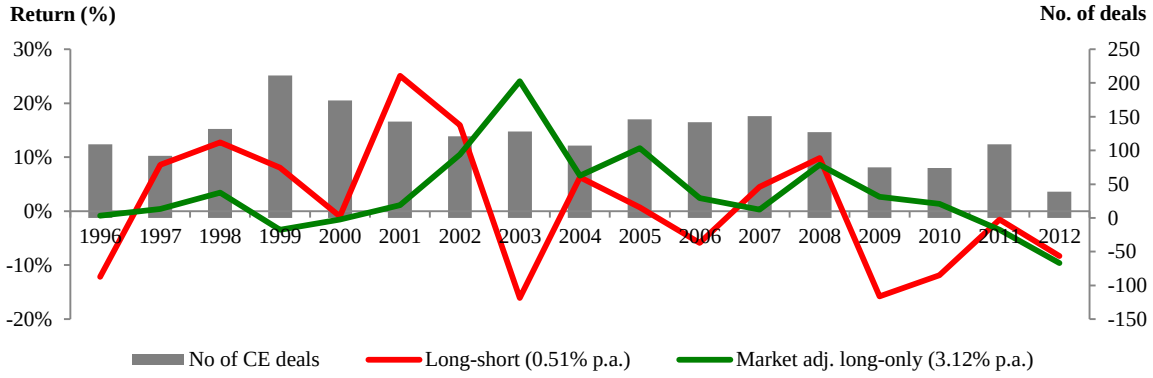


Fig 13. Takeover prediction portfolio returns (1996-2012). The three charts illustrate the analysis of takeover probability ranked decile portfolios for the European (chart 1), UK(chart 2) and Continental European (chart 3) sample. A market adjusted long-only portfolio for high takeover probability and a long-short portfolio with a long position in the high takeover probability portfolio and a short position in the low probability portfolio are calculated for 1996-2012. Stock returns for the 23,005 observations of the estimation and hold-out sample are retrieved from Blooomberg. The number of takeovers is presented on the secondary axis. It shows the number of takeovers in the largest 16 M&A markets in Europe (chart 1), in the UK (chart 2) and in the largest 15 M&A markets in Europe excluding the UK (chart 3). The takeover data match the raw data of the analysis and are retrieved from Thomson ONE.

As already observable in table 17, the still relatively low share of takeovers even in the high probability decile cannot be solely responsible for the generation of positive market-adjusted returns. Previous literature explains positive excess returns for the high takeover probability portfolios with the higher exposure to takeovers, rather than just the actual takeovers itself (see, e.g. Cremers, Nair & John, 2009, p. 1411). Cremers, Nair and John (2009) compress this into a "takeover factor", which helps explaining cross-sectional returns not captured by other factors like size, book-to-market or momentum in the Fama&French(1992) and Carhart(1997) models. Brar, Giamouridis and Liodakis (2009) point out that an outperformance of the market can also be caused by "capturing firms that benefit from merger speculation or rumors that may not necessarily end up in a takeover bid" (p. 447).

Consequently, the returns can be explained by the adjustment of the price for the current takeover probability and the expected premium, triggered by a takeover bid and/or takeover speculation. If the model is better at identifying potential takeover targets than the market, then an abnormal return can be generated in the high takeover probability portfolio, once prices are adjusted for the market's changed expectation of an implied takeover premium[39]. Hence, the profit is generated as $P= (q_2-q_1)*(S_1-S_2)$, where (q_2-q_1) is the difference between the market's new and old implied takeover probability and (S_1-S_2) is the expected premium in case of a takeover. The large return differences between the UK and CE can therefore be explained by either the level of the expected premium (S_1-S_2) or the change in the market's implied takeover probability (q_2-q_1). If the latter is the explanation, there are two scenarios. First, the UK's adjustment process from q_1 to q_2 is more efficient than for CE. This could mean that returns in the CE market are lower because for some firms it never adjusts prices for implied takeover probabilities, as it is not triggered by e.g. takeover speculation. The higher takeover speculation could be an indication for stronger market discipline in the UK. Second, the UK market's assessment of the implied takeover probability q is less efficient than for CE, which would imply that the takeover probability in CE is already priced in at the time of the investment.

[39] See chapter 3.2.1 for details.

6. Practical implications

The practical implications of the analyses in the previous chapters are plentiful. Other than the improved understanding of merger motives and the characteristics of potential targets, literature points out investment strategies, risk management and the identification of possible acquisition targets by strategic and financial investors as areas of application for takeover prediction models (see, e.g. Powell, 2001; Brar, Giamouridis & Liodakis, 2009). This chapter gives a detailed illustration of these areas of application, including the modeling of portfolio values over time for different investment strategies in the three regions.

6.1 Investment strategies

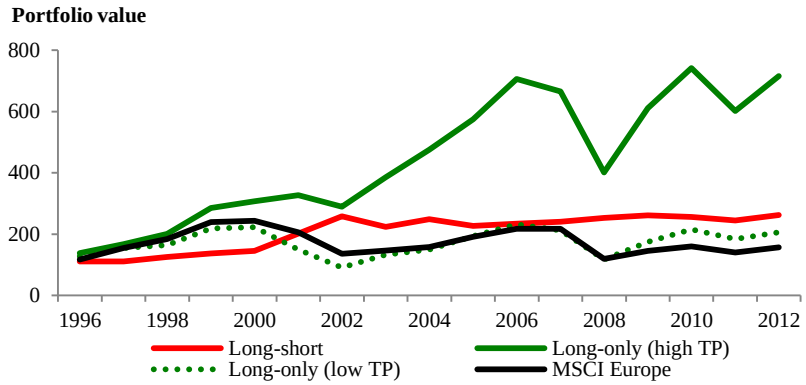
The development of a profitable investment strategy based on takeover prediction is one of the main areas of application for the analyses in this chapter. Various investment strategies for the exploitation of the advantages of a takeover prediction model are possible. Two of these are illustrated below and the performance development of the strategies is modeled for the time period from 1996 to 2012 (see figure 14).

Long-only investment in top 10% takeover probability firms

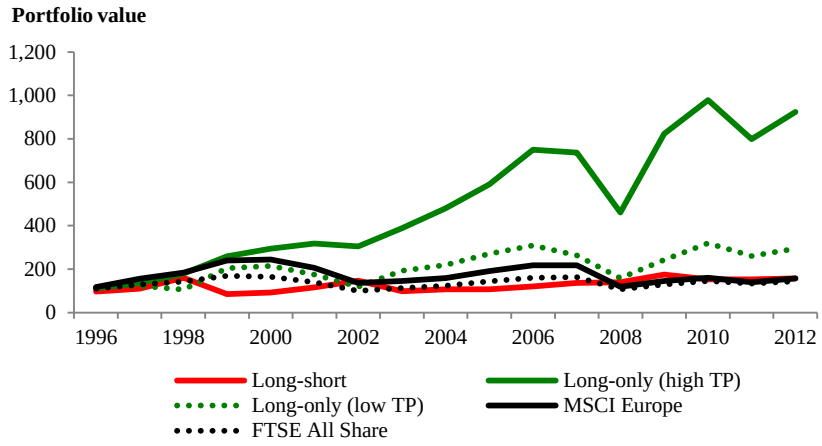
This strategy invests in the 10% of firms with the highest takeover probability at the beginning of each year. The analysis for the 17-year period from January 1996 to December 2012 in the previous chapter found market-adjusted compounded annual returns up to 13%. For the entire European sample these returns were 9.17% p.a. and for the Continental European market 3.12%. Hence, the strategy can be used by e.g. fund managers to improve their performance. Based on an investment of 100 in the beginning of 1996, the long-only strategy would have reached portfolio values of 716(r=13.09%), 923(r=14.90%) and 276(r=6.56%) for the European market, the UK and Continental Europe, respectively. As a comparison, the MSCI Europe would have reached 157 (r=2.84%) over that time period.

The practical implementation of the strategy through an equally weighted portfolio of firms is, at least on an institutional level, possible at a manageable cost. Due to the up to 178 stocks in the portfolio for the entire European market, there is rather limited applicability for private investors. An alternative to direct equity investments would be financial derivatives such as call options, which might however be limited by the supply of financial derivatives for all firms in the portfolio.

Europe



United Kingdom



Continental Europe

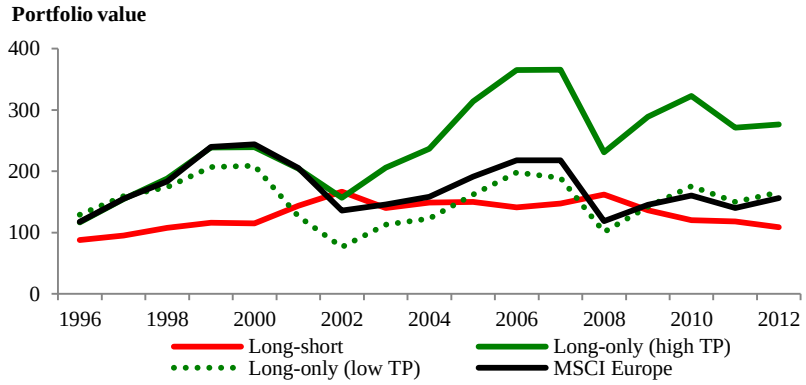


Fig 14. Portfolio development for takeover probability investment strategies. The development of yearly-rebalanced takeover probability portfolios with a basis of 100 on January 1st 1996 is shown for the period from 1996-2012. The long-only (high TP) is an equally weighted portfolio for the firms in the decile with the highest takeover probability(TP) for the specific year. The long only (low TP) is an equally weighted portfolio for the firms in the decile with the lowest takeover probability (TP) for the specific year and the long-short portfolio is a portfolio long in the high TP and short in the low TP portfolio. Stock prices were retrieved from Bloomberg. The models assume no transaction costs and no taxes.

Long-short portfolio of top and bottom 10% of takeover probability firms

This strategy goes long in the 10% of firms with the highest takeover probability and shorts the 10% with the lowest takeover probability at the beginning of each year. For the 17-year period, this strategy generated a compound annual return of 6.22%, 2.84% and 0.51% for the entire European, the UK and the Continental European sample, respectively. Hence, the strategy for Europe outperforms the MSCI Europe over that time period, is exactly on par for the UK and underperforms for the Continental European market. Therefore, the potential to generate potential profits is rather limited.

The practical implication of the strategy involves substantial transaction costs. In addition to equity positions for the long-portfolio, a large number of short positions for firms of various sizes have to be taken. This might limit the practical implication, as shorting of especially smaller stocks is often limited or subject to high costs.

The comparison of the two strategies shows that even though the volatility of the long-short position is lower as the market risk is cancelled out, the long-only strategy is more successful. Hence, institutional investors such as hedge or mutual funds could use this strategy to generate returns for their clients. A direct investment into this strategy for private investors is rather limited due to the number of firms in the portfolio and the potentially higher transactions costs for retail investors. An investment through investment funds or structured products could however be possible.

Several different alternative investment strategies using e.g. quintile portfolios or all expected takeover targets based on the cutoff probability approach could be employed and tested for the time period of the estimation and hold-out sample. However, due to the increasing number of stocks in the portfolio and a possible dilution of returns by adding baskets of shares with fewer takeovers, might limit the potential of the investor to generate returns from takeover prediction.

6.2 Other areas of application

Other areas of application for the prediction of takeovers and the assessment of takeover probabilities for publicly traded firms are e.g. in risk management for short-selling hedge funds. In addition, it is helpful in the identification of potential acquisition targets for executives of potential targets and potential acquirers and their respective advisors (e.g. investment bankers, consultants, etc.).

Hedge funds using short positions, expect the stock price to go down. However, if a sudden takeover speculation or the actual announcement of a takeover for the firm takes place, the short position can result in substantial losses. Due to the unlimited loss potential of a short position, a major financial setback for the hedge fund may result through the ignorance towards a potential acquisition. Even though, a major amount of research is conducted before entering into these positions, the insights about factors that influence takeover probability and the likelihood of a takeover itself can provide useful tools for institutional investors.

The ability to identify potential targets or at least firms with above-average takeover exposure might be used as a tool to generate e.g. long-list versions of potential acquisition targets for strategic and financial investors. These can then be used to conduct detailed research on the potential targets. Hence, takeover prediction can be used as a tool to lower search costs, for acquirers as well as their advisors.

The assessment of the own takeover likelihood is also useful for the managers of potential targets. Even though they should be the ones to know the firm better than anyone else, the quantification of takeover probability and its influence factors could give further insights for decisions. Based on this knowledge, they can change the strategic position of the company. Furthermore, corporate advisors such as investment bankers, consultants or lawyers can use takeover prediction to help their current clients with these decisions or scout for new clients that might need advise on related issues.

7. Conclusion

Previous empirical studies suggest that the prediction of takeover targets based on the theoretical knowledge from the market for corporate control is possible to a certain degree. The high announcement returns to target shareholders after a takeover bid make this task desirable from an investment perspective. This thesis analyzed the factors and potential for takeover prediction as well as the investment strategies based on takeover probabilities for the European market. Hereby, the period from 1996 to 2012, including the fifth and sixth merger wave, was studied. Furthermore, the often-assumed differences between the takeover market in the United Kingdom (UK) and Continental Europe (CE) were analyzed.

The findings of this thesis can be separated into two streams of results: first, the takeover prediction model, its factors and the predictive power of the model; second, the possibility to generate abnormal returns based on takeover prediction.

The takeover prediction model was estimated based on the common methodology of a logit regression and extended by a matching of year and industry code of the observations towards a conditional logit regression approach. An estimation sample of 856 target and 18,808 non-target observations for a 15-year period from 1996 to 2010 was used to estimate a takeover prediction model. Based on the suggestions by Palepu (1986), the eight hypotheses *inefficient management, firm size, growth-resource imbalance, undervaluation, industry disturbance, leverage, liquidity* and *investment behavior* were integrated into the model. T-tests for differences in the sample means and a correlation analysis helped to identify nine variables plus a dummy variable for UK firms to use in the prediction model.

The results of the conditional logit regression confirm the *inefficient management hypothesis* with a negative influence of sales growth and EBITDA-margin on takeover probability. Furthermore, the expectation of lower financial liquidity in terms of current ratio for takeover targets in the *liquidity hypothesis* was validated. Contrary to the theoretical and empirical expectations in the *undervaluation* and *industry disturbance hypothesis*, a positive influence of the P/E-ratio and a negative influence of takeover activity in the same industry were found. The introduced UK-dummy also shows a significant positive influence on takeover probability. The out-of-sample test, using the hold-out sample of 3,470 firm observations for 2011 and 2012 gives a predictive accuracy of 75.5%. The developed prediction model correctly predicts 54% of the targets and 76% of the non-targets in the out-of-sample test, using a cutoff probability of 18%. A ranking of firms in the out-of-sample test by takeover probability further shows that 28.6% of the targets are in the decile with the highest assessed takeover probability and 50% are in the top quintile. These results indicate a fairly good predictive power of the model.

The ability to generate abnormal returns based on the takeover prediction model was studied as a second part of the analysis. An event study for the target firms of the estimation sample finds a statistically significant cumulative average abnormal return for the target shareholders of 24.9% for an event window from 50 trading days before, until 50 trading days after the announcement of the takeover. However, a substantial difference in returns between UK targets and CE targets was found. To

examine the influence of the non-deal-specific factors used in the prediction model on cumulative abnormal returns (CAR), a multivariate regression model was used. A significant negative influence of EBITDA-margins and the industry disturbance dummy was found, while the P/E-ratio and the UK-dummy have a significantly positive influence on CAR. Since, the sign of the coefficients is the same for takeover probability and CAR, a correlation analysis was used to confirm a positive correlation between the two models. Even though a negative influence could be expected if the market was able to price the likelihood of a takeover far in advance, this gives an indication that a significant positive influence of takeover probability on the 20-trading-day run-up returns is observable. Hence, a high takeover probability goes along with higher price adjustments during the month before the takeover.

Based on the assessed takeover probabilities the yearly returns of the observations in the estimation and hold-out sample were used to analyze a return generation potential for takeover probability-driven investment strategies. A yearly rebalanced long position in the high takeover probability decile was found to generate a market-adjusted compound annual return of 9.7%, 11.3% and 3.1% over the last 17 years (1996-2012) for the European, UK and CE market, respectively. A long-short portfolio strategy reaches 6.22% for the European sample. As argued in previous studies, these returns are not only caused by takeover premiums, but also the exposure to takeovers, which may lead to takeover speculation without a subsequent bid. Returns are, therefore, generated through the price adjustments of the market's changed assessment of a firm's takeover probability and potential takeover premium. Hence, the observed differences in investment returns in the UK and CE could be explained by the efficiency of the market's adjustment to new takeover probability expectations, the efficiency of pre-investment implied takeover probabilities and the level of expected takeover premiums. Higher takeover speculation as a trigger of adjustment processes in the market's assessment of takeover probability and expected premium might be as sign for stronger market discipline in the UK compared to CE.

The findings of this thesis indicate that it is possible to substantially increase the chances of identifying takeover targets through the developed prediction model. In addition to the implementation of successful investment strategies, the application areas for the prediction model are for example in risk management for short positions of hedge funds and for the identification of potential takeover targets for strategic and financial investors. The applicability of the prediction model is, however, limited to the prediction of takeovers, which are explained by the theories of the market for corporate control. Therefore, this prediction model may miss takeovers with considerably different motives.

Further research may give an explanation of the exact portion of returns generated based on announcement returns of predicted takeover targets and returns as a result of price adjustments for the market's expectation of an implied expected takeover premium. Also, the contribution of the level of the expected premium in case of a takeover bid and the change in the market's implied takeover probability as components of the implied expected takeover premium could give further insights on market efficiency with regard to takeover exposure. Subsequently, the returns of takeover probability portfolios as a result of these market inefficiencies could be addressed and further explained. Moreover, the prediction model could be modified to predict specific types of targets, such as LBO or hostile targets.

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Appendix

Appendix A: Sample and Variables

A1 Sample composition – Targets & Non-targets

By year

	1996	1997	1998	1999	2000	2001	2002	2003
Targets	33	50	75	111	97	53	42	58
Non-Targets	554	650	721	889	1'040	1'210	1'246	1'225

	2004	2005	2006	2007	2008	2009	2010	Total
Targets	43	61	43	66	53	31	40	856
Non-Targets	1'336	1'432	1'548	1'690	1'820	1'705	1'742	18'808

By country

	Targets		Non-targets	
United Kingdom	518	60.51%	6'498	34.55%
France	131	15.30%	4'226	22.47%
Germany	99	11.57%	4'608	24.50%
Sweden	77	9.00%	1'733	9.21%
Switzerland	31	3.62%	1'743	9.27%
Total	856	100.00%	18'808	100.00%

A2 Description of variables & outlier elimination procedure

The data used for the analyses is retrieved and eliminated in the same way for all analyses. All observations, which do not give values for the variables below, were eliminated from the analysis.
Variables by hypothesis:

Inefficient Management

Sales growth (CAGR1):

Details: Sales growth from t-1 to t calculated as Sales(t) / Sales (t-1)
Source: Calculated on basis of sales data: Data retrieved from Thomson ONE for targets; Bloomberg for non-targets.
Elimination: Observations were dropped for values smaller than -80% or larger than +5000%.

Sales growth (CAGR2):

Details: Sales growth from t-2 to t calculated as $[(Sales(t) / Sales(t-2))^{(1/2)}-1]$
Source: Calculated on basis of sales data: Data retrieved from Thomson ONE for targets; Bloomberg for non-targets.
Elimination: Observations were dropped for values smaller than -80% or larger than +5000%.

EBITDA-margin (EBITDAMARGIN):

Details: Ratio of Earnings before interest, taxes, depreciation and amortization (EBITDA) to sales
Source: Calculated on basis of EBITDA and sales data: Data retrieved from Thomson ONE for targets; Bloomberg for non-targets.
Elimination: Observations were dropped from values smaller than -1,500% or larger than +500%.

Return on Equity (ROE):

Details: Ratio of net income to common equity(book value of equity).
Source: Calculated on basis of net income and common equity data: Data retrieved from Thomson ONE for targets; Bloomberg for non-targets
Elimination: Observations were dropped for values smaller than -500% or larger than 1000%. 1st percentile of the prediction sample was -400%, 99th at 217%.

Asset turnover (ASSETTURN:

Details: Sales to total assets.
Source: Calculated on basis of sales and totasl asset data: Data retrieved from Thomson ONE for targets; Bloomberg for non-targets
Elimination: Observations were dropped for values larger than 10. The 99th percentile for prediction sample was 3.97.

Firm size

Sales (SALES1 / LNSALES):

Details: Sales (in $m) according to income statement. ln(sales) was calculated as the natural logarithm of sales.
Source: Data retrieved from Thomson ONE for targets; Bloomberg for non-targets
Elimination: Observations were dropped for sales values less than $5m.

Market capitalization (EQV/ LNEQV):

Details: Market capitalization (in $m) at the end of the financial year. ln(eqv) was calculated as the natural logarithm of market capitalization (=equity value(EQV)).
Source: Data retrieved from Thomson ONE for targets; Bloomberg for non-targets.
Elimination: Observations were dropped for values below $10m.

Total assets (TOTASS/ LNTOTASS):

Details: Book value of total assets (in $m) according to income statement. ln(totass) was calculated as the natural logarithm of total assets.
Source: Data retrieved from Thomson ONE for targets; Bloomberg for non-targets.
Elimination: No elimination applied to total assets as elimination of the other size variables already gives a suitable sample with regard to total assets.

Growth resource

Growth resource imbalance dummy (GRDUMMY):

Details: Defined as a dummy variable based on growth (2-year-sales-CAGR) and financial resources (leverge=debt/equity and liquidity=cash & marketable securities / total assets). Growth, leverage and liquidity is compared to the average values for the year of the observation in the sample. GRDUMMY=1 if growth> average growth & leverage> average leverage & liquidity< average liquidity or if growth< average growth & leverage< average leverage & liquidity> average liquidity.
Source: Based on sales as well as book values for total debt, total equity, cash & marketable securities and total assets. Data retrieved from Thomson ONE for targets; Bloomberg for non-targets.
Elimination: Not applicable.

Undervaluation

Price-to-earnings ratio (PE):

Details: Price to earnings ratio calculated as market capitalization to net income.
Source: Calculated on basis of earnings and market capitalization at the end of the financial year. Data retrieved from Thomson ONE for targets; Bloomberg for non-targets.
Elimination: Observations were dropped for values smaller than -200 or larger than +500.

Market-to-book ratio (MB):

Details: Market of equity (market capitalization) to book value of total assets.
Source: Data retrieved from Thomson ONE for targets; Bloomberg for non-targets
Elimination: Observations were dropped for values smaller than 0 or larger than 20.

Industry disturbance

Industry disturbance dummy (INDDIS4DMY):

Details: Defined as a dummy variable based on the fact that a takeover took place in the same industry (same 4-digit standard industry classification (SIC) code) during the previous year. Based on the raw list of deals including 4,742 takeovers for all European countries from 1985-2012. INDDIS4DMY=1 if there was at least one deal in the same industry the year before.
Source: Data retrieved from Thomson ONE.
Elimination: Not applicable.

Liquidity

Cash/total assets (LIQUIDITY):

Details: Book value of cash & marketable securites to total assets.
Source: Data retrieved from Thomson ONE for targets; Bloomberg for non-targets

Current ratio (CURRAT):

Details: Book values of current assets to current liabilities.
Source: Data retrieved from Thomson ONE for targets; Bloomberg for non-targets
Elimination: Observations were dropped for values larger than 20.

Leverage

Leverage (LEVERAGE):

Details: Book value of debt to equity.
Source: Data retrieved from Thomson ONE for targets; Bloomberg for non-targets.
Elimination: Observations were dropped for values larger than 99.

Investment behavior

CAPEX / Sales (CAPEXSALES):

Details: CAPEX according to cash flow statement to sales according to income statement.
Source: Data retrieved from Thomson ONE for targets; Bloomberg for non-targets.
Elimination: Observations were dropped for values larger than 100%.

A3 Descriptive statistics (STATA-Output)

Target sample

Variable	Obs	Mean	Std. Dev.	Min	Max
cagr1	856	.1401686	.6199468	-.7172353	11.53172
cagr2	856	.1749444	.6650116	-.51805	15.46056
ebitdamargin	856	.1040632	.2150279	-2.663133	.8615919
roe	856	.0837869	.5985226	-4.714198	7.674972
assetturn	856	1.309951	.8495829	.0394489	8.832267
totass	856	1358.454	5285.452	4.185	93707.23
sales1	856	1233.531	4506.256	5.419	88844.45
eqv	856	1405.618	5936.911	10.162	75955.93
pe	856	20.7782	50.61408	-192.8829	444.48
mb	856	1.305573	1.393866	.0049296	14.04428
grdummy	856	.2429907	.4291402	0	1
leverage	856	.3489602	.4971894	.0001597	6.015206
liquidity	856	.1153772	.1326009	.0000328	.8566286
currat	856	1.050852	1.06048	.0446489	18.01416
capexsales	856	.0735938	.1109467	.0006627	.9057833
inddis4dmy	856	.2558411	.436588	0	1

Non-target sample

Variable	Obs	Mean	Std. Dev.	Min	Max
cagr1	18808	.2233172	.9261278	-.7979296	48.57396
cagr2	18808	.3358899	1.267269	-.7675154	43.91958
ebitdamargin	18808	.1033437	.2671177	-12.39195	3.095169
roe	18808	.0743539	.5245845	-4.979008	9.670677
assetturn	18808	1.172792	.7269965	.031042	9.516869
totass	18808	3675.027	15971.16	2.4466	366913.7
sales1	18808	2922.074	11531.69	5.0043	361143
eqv	18808	2816.936	12761.83	10.0025	414795.6
pe	18808	16.28635	41.64135	-199.246	498.0986
mb	18808	1.116873	1.329469	.0062544	18.98669
grdummy	18808	.2708422	.4444066	0	1
leverage	18808	.3235601	.5609506	0	41.13369
liquidity	18808	.1411598	.1464299	0	.9420121
currat	18808	1.813429	1.443084	.0396239	19.32611
capexsales	18808	.0634724	.0944144	0	.985172
inddis4dmy	18808	.452786	.4977791	0	1

Appendix B: Analyses – Prediction Model

(STATA-File: Thesis_v12.do)

B1 Two sample t-tests (STATA-Output)

```
.
. ttest cagr1, by(targetdummy)

Two-sample t test with equal variances

   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |   18808    .2233172     .006753    .9261278    .2100806    .2365537
       1 |     856    .1401686    .0211893    .6199468    .0985794    .1817578
---------+--------------------------------------------------------------------
combined |   19664    .2196976    .0065256     .915081    .2069068    .2324884
---------+--------------------------------------------------------------------
    diff |            .0831486     .031976                .020473    .1458242
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =   2.6003
Ho: diff = 0                     degrees of freedom =    19662

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9953         Pr(|T| > |t|) = 0.0093          Pr(T > t) = 0.0047

. ttest cagr2, by(targetdummy)

Two-sample t test with equal variances

   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |   18808    .3358899    .0092405    1.267269    .3177776    .3540022
       1 |     856    .1749444    .0227296    .6650116     .130332    .2195568
---------+--------------------------------------------------------------------
combined |   19664    .3288837    .0088965    1.247544    .3114458    .3463216
---------+--------------------------------------------------------------------
    diff |            .1609455    .0435857                .0755139    .2463771
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =   3.6926
Ho: diff = 0                     degrees of freedom =    19662

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9999         Pr(|T| > |t|) = 0.0002          Pr(T > t) = 0.0001

. ttest ebitdamargin, by(targetdummy)

Two-sample t test with equal variances

   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |   18808    .1033437    .0019477    .2671177    .0995259    .1071614
       1 |     856    .1040632    .0073495    .2150279     .089638    .1184884
---------+--------------------------------------------------------------------
combined |   19664     .103375    .0018902    .2650588     .09967    .1070799
---------+--------------------------------------------------------------------
    diff |           -.0007196    .0092636               -.018877    .0174379
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  -0.0777
Ho: diff = 0                     degrees of freedom =    19662

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.4690         Pr(|T| > |t|) = 0.9381          Pr(T > t) = 0.5310
```

```
. ttest roe, by(targetdummy)

Two-sample t test with equal variances

   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |   18808    .0743539    .0038251    .5245845    .0668563    .0818514
       1 |     856    .0837869    .0204571    .5985226    .0436349    .1239389
---------+--------------------------------------------------------------------
combined |   19664    .0747645    .0037653    .5280051    .0673841    .0821448
---------+--------------------------------------------------------------------
    diff |           -.0094331    .0184533               -.0456031     .026737
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  -0.5112
Ho: diff = 0                                     degrees of freedom =    19662

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.3046         Pr(|T| > |t|) = 0.6092          Pr(T > t) = 0.6954


. ttest assetturn, by(targetdummy)

Two-sample t test with equal variances

   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |   18808    1.172792     .005301    .7269965    1.162401    1.183182
       1 |     856    1.309951    .0290381    .8495829    1.252956    1.366945
---------+--------------------------------------------------------------------
combined |   19664    1.178762    .0052291    .7332695    1.168513    1.189012
---------+--------------------------------------------------------------------
    diff |           -.1371591    .0256086               -.1873542   -.0869641
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  -5.3560
Ho: diff = 0                                     degrees of freedom =    19662

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

. ttest sales1, by(targetdummy)

Two-sample t test with equal variances

   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |   18808    2922.074    84.08563    11531.69    2757.258    3086.889
       1 |     856    1233.531    154.0207    4506.256     931.228    1535.834
---------+--------------------------------------------------------------------
combined |   19664    2848.569    80.74125    11322.21    2690.309    3006.829
---------+--------------------------------------------------------------------
    diff |            1688.543    395.5205                913.2891    2463.796
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =   4.2692
Ho: diff = 0                                     degrees of freedom =    19662

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

. ttest eqv, by(targetdummy)

Two-sample t test with equal variances

   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |   18808    2816.936     93.0554    12761.83    2634.539    2999.333
       1 |     856    1405.618    202.9194    5936.911     1007.34    1803.897
---------+--------------------------------------------------------------------
combined |   19664    2755.499    89.46482    12545.51    2580.141    2930.858
---------+--------------------------------------------------------------------
    diff |            1411.317    438.3415                552.131    2270.504
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =   3.2197
Ho: diff = 0                                     degrees of freedom =    19662

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9994         Pr(|T| > |t|) = 0.0013          Pr(T > t) = 0.0006
```

```
. ttest totass, by(targetdummy)

Two-sample t test with equal variances

   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |   18808    3675.027    116.4569    15971.16    3446.761    3903.293
       1 |     856    1358.454     180.653    5285.452    1003.879     1713.03
---------+--------------------------------------------------------------------
combined |   19664    3574.184     111.715    15665.62    3355.213    3793.155
---------+--------------------------------------------------------------------
    diff |            2316.573    547.2535                1243.91    3389.236
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =   4.2331
Ho: diff = 0                     degrees of freedom =    19662

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

. ttest grdummy, by(targetdummy)

Two-sample t test with equal variances

   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |   18808    .2708422    .0032405    .4444066    .2644906    .2771938
       1 |     856    .2429907    .0146677    .4291402    .2142017    .2717796
---------+--------------------------------------------------------------------
combined |   19664    .2696298    .0031647    .4437787    .2634267    .2758328
---------+--------------------------------------------------------------------
    diff |            .0278515    .0155085               -.0025464    .0582495
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =   1.7959
Ho: diff = 0                     degrees of freedom =    19662

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9637         Pr(|T| > |t|) = 0.0725          Pr(T > t) = 0.0363

. ttest pe, by(targetdummy)

Two-sample t test with equal variances

   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |   18808    16.28635    .3036362    41.64135     15.6912    16.88151
       1 |     856     20.7782    1.729953    50.61408    17.38274    24.17365
---------+--------------------------------------------------------------------
combined |   19664    16.48189    .3000837    42.08026     15.8937    17.07008
---------+--------------------------------------------------------------------
    diff |           -4.491844    1.470328               -7.373811   -1.609878
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  -3.0550
Ho: diff = 0                     degrees of freedom =    19662

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0011         Pr(|T| > |t|) = 0.0023          Pr(T > t) = 0.9989

. ttest mb, by(targetdummy)

Two-sample t test with equal variances

   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |   18808    1.116873    .0096941    1.329469    1.097871    1.135874
       1 |     856    1.305573    .0476414    1.393866    1.212066    1.399081
---------+--------------------------------------------------------------------
combined |   19664    1.125087    .0095049    1.332857    1.106457    1.143717
---------+--------------------------------------------------------------------
    diff |           -.1887006     .046563               -.2799681   -.0974332
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  -4.0526
Ho: diff = 0                     degrees of freedom =    19662

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0001          Pr(T > t) = 1.0000
```

```
. ttest leverage, by(targetdummy)

Two-sample t test with equal variances

   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |   18808    .3235601    .0040903    .5609506    .3155428    .3315774
       1 |     856    .3489602    .0169936    .4971894    .3156062    .3823142
---------+--------------------------------------------------------------------
combined |   19664    .3246658    .0039816    .5583392    .3168615    .3324702
---------+--------------------------------------------------------------------
    diff |           -.0254001    .0195127               -.0636467    .0128465
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  -1.3017
Ho: diff = 0                     degrees of freedom =    19662

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0965         Pr(|T| > |t|) = 0.1930          Pr(T > t) = 0.9035

. ttest liquidity, by(targetdummy)

Two-sample t test with equal variances

   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |   18808    .1411598    .0010677    .1464299    .1390669    .1432526
       1 |     856    .1153772    .0045322    .1326009    .1064816    .1242727
---------+--------------------------------------------------------------------
combined |   19664    .1400374    .0010408     .145947    .1379974    .1420774
---------+--------------------------------------------------------------------
    diff |            .0257826    .0050974               .0157912     .035774
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =   5.0580
Ho: diff = 0                     degrees of freedom =    19662

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

. ttest currat, by(targetdummy)

Two-sample t test with equal variances

   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |   18808    1.813429    .0105225    1.443084    1.792804    1.834054
       1 |     856    1.050852    .0362465     1.06048    .9797094    1.121994
---------+--------------------------------------------------------------------
combined |   19664    1.780233    .0102475    1.436993    1.760147    1.800319
---------+--------------------------------------------------------------------
    diff |             .762577    .0499266               .6647166    .8604374
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  15.2740
Ho: diff = 0                     degrees of freedom =    19662

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

. ttest capexsales, by(targetdummy)

Two-sample t test with equal variances

   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
       0 |   18808    .0634724    .0006884    .0944144     .062123    .0648218
       1 |     856    .0735938    .0037921    .1109467    .0661509    .0810367
---------+--------------------------------------------------------------------
combined |   19664     .063913     .000679     .095213    .0625821    .0652439
---------+--------------------------------------------------------------------
    diff |           -.0101214    .0033268               -.0166423   -.0036005
------------------------------------------------------------------------------
    diff = mean(0) - mean(1)                                      t =  -3.0423
Ho: diff = 0                     degrees of freedom =    19662

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0012         Pr(|T| > |t|) = 0.0024          Pr(T > t) = 0.9988
```

```
. ttest inddis4dmy, by(targetdummy)

Two-sample t test with equal variances
```

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	18808	.452786	.0036297	.4977791	.4456716	.4599005
1	856	.2558411	.0149223	.436588	.2265525	.2851297
combined	19664	.4442128	.0035434	.4968907	.4372673	.4511582
diff		.1969449	.0173091		.1630176	.2308722

```
    diff = mean(0) - mean(1)                                      t =  11.3781
Ho: diff = 0                     degrees of freedom =    19662

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

```
. ttest inddis4, by(targetdummy)

Two-sample t test with equal variances
```

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	18808	1.604211	.0253702	3.479323	1.554483	1.653939
1	856	1.334112	.0968886	2.834715	1.143945	1.524279
combined	19664	1.592453	.0246323	3.454148	1.544172	1.640735
diff		.2700988	.1207048		.0335073	.5066904

```
    diff = mean(0) - mean(1)                                      t =   2.2377
Ho: diff = 0                     degrees of freedom =    19662

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9874         Pr(|T| > |t|) = 0.0253          Pr(T > t) = 0.0126
```

B2 Correlation matrix (STATA-Output)

```
. pwcorr cagr1 cagr2 ebitdamargin roe assetturn lntotass lnsales lneqv pe mb grdummy leverage liquidity currat capexsales inddis4dmy ukdummy, sig star(0.05
> )
```

	cagr1	cagr2	ebitda~n	roe	assett~n	lntotass	lnsales	lneqv	pe	mb	grdummy	leverage	liquid~y	currat	capexs~s	inddis~y	ukdummy
cagr1	1.0000																
cagr2	0.2489*	1.0000															
	0.0000																
ebitdamargin	-0.0689*	-0.0364*	1.0000														
	0.0000	0.0000															
roe	-0.0005	0.0050	0.1983*	1.0000													
	0.9395	0.4858	0.0000														
assetturn	-0.0246*	0.0422*	-0.0568*	0.0730*	1.0000												
	0.0005	0.0000	0.0000	0.0000													
lntotass	-0.0608*	-0.0416*	0.1569*	0.0754*	-0.1646*	1.0000											
	0.0000	0.0000	0.0000	0.0000	0.0000												
lnsales	-0.0806*	-0.0390*	0.1663*	0.1024*	0.1083*	0.9523*	1.0000										
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000											
lneqv	-0.0217*	-0.0150*	0.1611*	0.1265*	-0.1500*	0.9041*	0.8601*	1.0000									
	0.0023	0.0359	0.0000	0.0000	0.0000	0.0000	0.0000										
pe	0.0065	-0.0023	0.0914*	0.0664*	-0.0145*	0.0156*	0.0151*	0.0726*	1.0000								
	0.3649	0.7473	0.0000	0.0000	0.0423	0.0288	0.0341	0.0000									
mb	0.0896*	0.0565*	-0.0397*	0.0714*	0.0263*	-0.1846*	-0.1789*	0.1628*	0.1248*	1.0000							
	0.0000	0.0000	0.0000	0.0000	0.0002	0.0000	0.0000	0.0000	0.0000								
grdummy	-0.0069	-0.0139	-0.0158*	0.0030	-0.0294*	-0.0896*	-0.0975*	-0.0388*	-0.0012	0.0658*	1.0000						
	0.3344	0.0520	0.0265	0.6776	0.0000	0.0000	0.0000	0.0000	0.8673	0.0000							
leverage	-0.0215*	-0.0228*	0.0842*	0.0100	-0.0999*	0.1510*	0.1118*	0.0520*	-0.0184*	-0.1301*	-0.0893*	1.0000					
	0.0025	0.0014	0.0000	0.1614	0.0000	0.0000	0.0000	0.0000	0.0099	0.0000	0.0000						
liquidity	0.0586*	0.0280*	-0.2045*	-0.0089	-0.0868*	-0.2406*	-0.2813*	-0.0889*	0.0043	0.3332*	0.3476*	-0.2024*	1.0000				
	0.0000	0.0001	0.0000	0.2114	0.0000	0.0000	0.0000	0.0000	0.5456	0.0000	0.0000	0.0000					
currat	0.0360*	0.0053	-0.1516*	-0.0234*	-0.1658*	-0.2233*	-0.2903*	-0.1249*	-0.0037	0.1930*	0.1855*	-0.1640*	0.5590*	1.0000			
	0.0000	0.4544	0.0000	0.0010	0.0000	0.0000	0.0000	0.0000	0.6086	0.0000	0.0000	0.0000	0.0000				
capexsales	0.0642*	0.0457*	0.0799*	-0.0238*	-0.3309*	0.0665*	-0.0711*	0.0766*	0.0098	0.0127	-0.0136	0.0891*	-0.0473*	-0.0020	1.0000		
	0.0000	0.0000	0.0000	0.0008	0.0000	0.0000	0.0000	0.0000	0.1698	0.0748	0.0558	0.0000	0.0000	0.7803			
inddis4dmy	0.0166*	0.0282*	-0.0234*	-0.0320*	-0.0661*	-0.0407*	-0.0722*	0.0032	0.0113	0.0950*	0.0302*	-0.0414*	0.1239*	0.0380*	0.0553*	1.0000	
	0.0196	0.0001	0.0010	0.0000	0.0000	0.0000	0.0000	0.6486	0.1122	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
ukdummy	0.0140	0.0143*	0.0423*	0.0375*	0.0845*	-0.0600*	-0.0494*	0.0048	-0.0350*	0.0800*	-0.0172*	-0.0420*	-0.0678*	-0.0935*	0.0386*	-0.0018	1.0000
	0.0502	0.0443	0.0000	0.0000	0.0000	0.0000	0.0000	0.4979	0.0000	0.0000	0.0161	0.0000	0.0000	0.0000	0.0000	0.7968	

```
. pwcorr cagr2 ebitdamargin roe assetturn lntotass lnsales lneqv pe mb grdummy leverage liquidity currat capexsales inddis4dmy ukdummy, sig star(0.05)
```

	cagr2	ebitda~n	roe	assett~n	lntotass	lnsales	lneqv	pe	mb	grdummy	leverage	liquid~y	currat	capexs~s	inddis~y	ukdummy
cagr2	1.0000															
ebitdamargin	-0.0364* 0.0000	1.0000														
roe	0.0050 0.4858	0.1983* 0.0000	1.0000													
assetturn	0.0422* 0.0000	-0.0568* 0.0000	0.0730* 0.0000	1.0000												
lntotass	-0.0416* 0.0000	0.1569* 0.0000	0.0754* 0.0000	-0.1646* 0.0000	1.0000											
lnsales	-0.0390* 0.0000	0.1663* 0.0000	0.1024* 0.0000	0.1083* 0.0000	0.9523* 0.0000	1.0000										
lneqv	-0.0150* 0.0359	0.1611* 0.0000	0.1265* 0.0000	-0.1500* 0.0000	0.9041* 0.0000	0.8601* 0.0000	1.0000									
pe	-0.0023 0.7473	0.0914* 0.0000	0.0664* 0.0000	-0.0145* 0.0423	0.0156* 0.0288	0.0151* 0.0341	0.0726* 0.0000	1.0000								
mb	0.0565* 0.0000	-0.0397* 0.0000	0.0714* 0.0000	0.0263* 0.0002	-0.1846* 0.0000	-0.1789* 0.0000	0.1628* 0.0000	0.1248* 0.0000	1.0000							
grdummy	-0.0139 0.0520	-0.0158* 0.0265	0.0030 0.6776	-0.0294* 0.0000	-0.0896* 0.0000	-0.0975* 0.0000	-0.0388* 0.0000	-0.0012 0.8673	0.0658* 0.0000	1.0000						
leverage	-0.0228* 0.0014	0.0842* 0.0000	0.0100 0.1614	-0.0999* 0.0000	0.1510* 0.0000	0.1118* 0.0000	0.0520* 0.0000	-0.0184* 0.0099	-0.1301* 0.0000	-0.0893* 0.0000	1.0000					
liquidity	0.0280* 0.0001	-0.2045* 0.0000	-0.0089 0.2114	-0.0868* 0.0000	-0.2406* 0.0000	-0.2813* 0.0000	-0.0889* 0.0000	0.0043 0.5456	0.3332* 0.0000	0.3476* 0.0000	-0.2024* 0.0000	1.0000				
currat	0.0053 0.4544	-0.1516* 0.0000	-0.0234* 0.0010	-0.1658* 0.0000	-0.2233* 0.0000	-0.2903* 0.0000	-0.1249* 0.0000	-0.0037 0.6086	0.1930* 0.0000	0.1855* 0.0000	-0.1640* 0.0000	0.5590* 0.0000	1.0000			
capexsales	0.0457* 0.0000	0.0799* 0.0000	-0.0238* 0.0008	-0.3309* 0.0000	0.0665* 0.0000	-0.0711* 0.0000	0.0766* 0.0000	0.0098 0.1698	0.0127 0.0748	-0.0136 0.0558	0.0891* 0.0000	-0.0473* 0.0000	-0.0020 0.7803	1.0000		
inddis4dmy	0.0282* 0.0001	-0.0234* 0.0010	-0.0320* 0.0000	-0.0661* 0.0000	-0.0407* 0.0000	-0.0722* 0.0000	0.0032 0.6486	0.0113 0.1122	0.0950* 0.0000	0.0302* 0.0000	-0.0414* 0.0000	0.1239* 0.0000	0.0380* 0.0000	0.0553* 0.0000	1.0000	
ukdummy	0.0143* 0.0443	0.0423* 0.0000	0.0375* 0.0000	0.0845* 0.0000	-0.0600* 0.0000	-0.0494* 0.0000	0.0048 0.4979	-0.0350* 0.0000	0.0800* 0.0000	-0.0172* 0.0161	-0.0420* 0.0000	-0.0678* 0.0000	-0.0935* 0.0000	0.0386* 0.0000	-0.0018 0.7968	1.0000

B3 Logit Regressions (STATA-Output)

Conditional logit regression matched by year of observation and industry code (SIC):

All variables

```
. //Tests
. clogit targetdummy cagr1 cagr2 ebitdamargin roe assetturn lntotass lnsales lneqv pe mb leverage currat capexsales grdummy inddis4dmy, group(match)
note: multiple positive outcomes within groups encountered.
note: 5940 groups (14923 obs) dropped because of all positive or
      all negative outcomes.

Iteration 0:   log likelihood = -734.86505
Iteration 1:   log likelihood = -688.11324
Iteration 2:   log likelihood = -686.65042
Iteration 3:   log likelihood = -686.64653
Iteration 4:   log likelihood = -686.64653

Conditional (fixed-effects) logistic regression   Number of obs   =       4741
                                                  LR chi2(15)     =     918.82
                                                  Prob > chi2     =     0.0000
Log likelihood = -686.64653                       Pseudo R2       =     0.4009

------------------------------------------------------------------------------
 targetdummy |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       cagr1 |  -.3801319   .1726382    -2.20   0.028    -.7184966   -.0417672
       cagr2 |  -.4930485    .131646    -3.75   0.000      -.75107   -.2350271
ebitdamargin |  -.7720849   .2378027    -3.25   0.001    -1.23817   -.3060002
         roe |   .0471332   .0983776     0.48   0.632    -.1456832    .2399497
  assetturn  |   .4607224   .1701952     2.71   0.007     .127146    .7942988
    lntotass |  -.2090465   .2538291    -0.82   0.410    -.7065423    .2884493
     lnsales |  -.6155902   .2282266    -2.70   0.007    -1.062906   -.1682744
       lneqv |   .6936116   .1349343     5.14   0.000     .4291453    .9580779
          pe |    .003026   .0011464     2.64   0.008     .0007791    .0052729
          mb |  -.0838302   .0762581    -1.10   0.272    -.2332933    .0656329
    leverage |  -.0886903   .1333025    -0.67   0.506    -.3499585    .1725778
     currat  |  -1.370881   .1149722   -11.92   0.000    -1.596223   -1.14554
  capexsales |  -.4204199   .7243063    -0.58   0.562    -1.840034    .9991944
    grdummy  |   .1515544    .140034     1.08   0.279    -.1229072    .426016
  inddis4dmy |  -4.825269   .3653734   -13.21   0.000    -5.541388   -4.10915
------------------------------------------------------------------------------
```

Selected variables - Three models

M1 – Basic model with 4 hypotheses + control for ukdummy

```
. //M1
. clogit targetdummy cagr2  ebitdamargin lneqv pe grdummy ukdummy, group(match)
note: multiple positive outcomes within groups encountered.
note: 5940 groups (14923 obs) dropped because of all positive or
      all negative outcomes.

Iteration 0:   log likelihood = -1069.1007
Iteration 1:   log likelihood = -1066.1479
Iteration 2:   log likelihood = -1066.1363
Iteration 3:   log likelihood = -1066.1363

Conditional (fixed-effects) logistic regression   Number of obs   =       4741
                                                  LR chi2(6)      =     159.84
                                                  Prob > chi2     =     0.0000
Log likelihood = -1066.1363                       Pseudo R2       =     0.0697

------------------------------------------------------------------------------
 targetdummy |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       cagr2 |  -.5529038   .1033384    -5.35   0.000    -.7554433   -.3503643
ebitdamargin |  -.3124289   .1497781    -2.09   0.037    -.6059887   -.0188692
       lneqv |   .0133595   .0262128     0.51   0.610    -.0380167    .0647357
          pe |   .0028821   .0009732     2.96   0.003     .0009747    .0047896
     grdummy |  -.1645869   .1106196    -1.49   0.137    -.3813973    .0522235
     ukdummy |   1.021925   .1033759     9.89   0.000     .8193115    1.224538
------------------------------------------------------------------------------
```

M2 – Basic model with 4 hypotheses + industrydummy + control for ukdummy

```
. //M2
. clogit targetdummy cagr2  ebitdamargin lneqv pe grdummy inddis4dmy ukdummy, group(match)
note: multiple positive outcomes within groups encountered.
note: 5940 groups (14923 obs) dropped because of all positive or
      all negative outcomes.

Iteration 0:   log likelihood = -856.03001
Iteration 1:   log likelihood = -781.78107
Iteration 2:   log likelihood =  -780.3081
Iteration 3:   log likelihood = -780.30374
Iteration 4:   log likelihood = -780.30374

Conditional (fixed-effects) logistic regression   Number of obs   =       4741
                                                  LR chi2(7)      =     731.51
                                                  Prob > chi2     =     0.0000
Log likelihood = -780.30374                       Pseudo R2       =     0.3191

------------------------------------------------------------------------------
 targetdummy |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       cagr2 |  -.6242472   .1225841    -5.09   0.000    -.8645076   -.3839868
ebitdamargin |  -.4918343   .1700464    -2.89   0.004    -.8251191   -.1585494
       lneqv |   .0241962    .031171     0.78   0.438    -.0368979    .0852903
          pe |   .0044625   .0011202     3.98   0.000     .0022669    .0066581
     grdummy |  -.2023988   .1299141    -1.56   0.119    -.4570258    .0522282
   inddis4dmy |    -5.1861   .3501409   -14.81   0.000    -5.872363   -4.499836
     ukdummy |   1.128344   .1231986     9.16   0.000     .8868786    1.369808
------------------------------------------------------------------------------
```

M3 – Complete Model

```
. //M3
. clogit targetdummy cagr2  ebitdamargin lneqv pe leverage currat capexsales grdummy inddis4dmy ukdummy, group(match)
note: multiple positive outcomes within groups encountered.
note: 5940 groups (14923 obs) dropped because of all positive or
      all negative outcomes.

Iteration 0:   log likelihood = -750.31172
Iteration 1:   log likelihood = -692.86748
Iteration 2:   log likelihood = -691.76855
Iteration 3:   log likelihood =  -691.7563
Iteration 4:   log likelihood = -691.75629

Conditional (fixed-effects) logistic regression   Number of obs   =       4741
                                                  LR chi2(10)     =     908.60
                                                  Prob > chi2     =     0.0000
Log likelihood = -691.75629                       Pseudo R2       =     0.3964
```

targetdummy	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
cagr2	-.554824	.1266923	-4.38	0.000	-.8031364	-.3065116
ebitdamargin	-.7048259	.2573495	-2.74	0.006	-1.209222	-.2004302
lneqv	-.0298083	.033262	-0.90	0.370	-.0950007	.0353841
pe	.0042158	.0011189	3.77	0.000	.0020228	.0064088
leverage	-.1756853	.132253	-1.33	0.184	-.4348964	.0835258
currat	-1.19257	.111559	-10.69	0.000	-1.411222	-.9739188
capexsales	.2000361	.6646812	0.30	0.763	-1.102715	1.502787
grdummy	.1643174	.1403771	1.17	0.242	-.1108165	.4394514
inddis4dmy	-4.893523	.3542972	-13.81	0.000	-5.587932	-4.199113
ukdummy	1.030509	.1295752	7.95	0.000	.7765466	1.284472

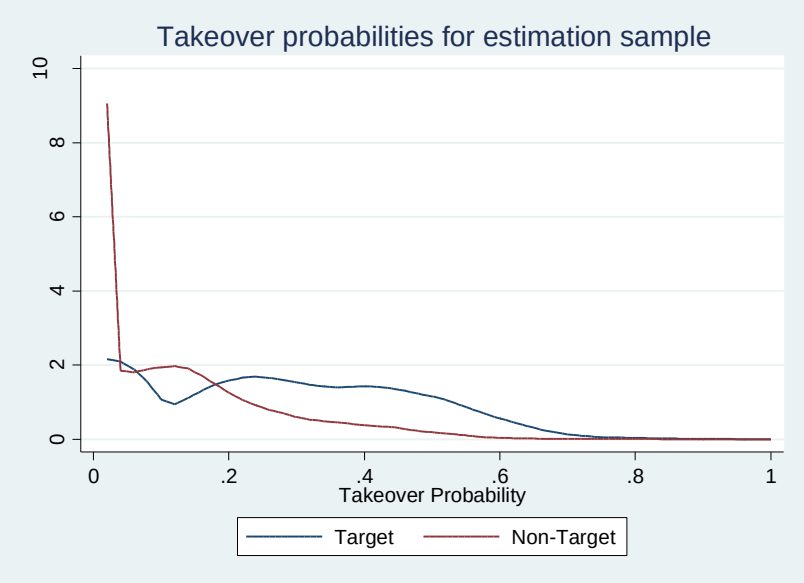
M3 – Complete Model without control for ukdummy

```
. // M3 without UK dummy
. clogit targetdummy cagr2  ebitdamargin lneqv pe leverage currat capexsales grdummy inddis4dmy, group(match)
note: multiple positive outcomes within groups encountered.
note: 5940 groups (14923 obs) dropped because of all positive or
      all negative outcomes.

Iteration 0:   log likelihood = -780.25587
Iteration 1:   log likelihood = -726.27295
Iteration 2:   log likelihood =  -725.0621
Iteration 3:   log likelihood = -725.05506
Iteration 4:   log likelihood = -725.05505

Conditional (fixed-effects) logistic regression   Number of obs   =       4741
                                                  LR chi2(9)      =     842.00
                                                  Prob > chi2     =     0.0000
Log likelihood = -725.05505                       Pseudo R2       =     0.3673
```

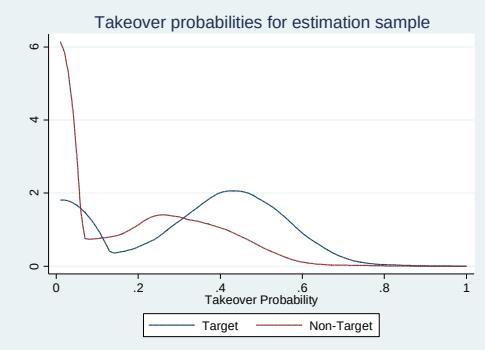
targetdummy	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
cagr2	-.561498	.1219367	-4.60	0.000	-.8004896	-.3225064
ebitdamargin	-.6618938	.2625109	-2.52	0.012	-1.176406	-.1473819
lneqv	-.0342997	.032397	-1.06	0.290	-.0977966	.0291973
pe	.0034339	.001102	3.12	0.002	.0012741	.0055938
leverage	-.2964816	.1289254	-2.30	0.021	-.5491707	-.0437924
currat	-1.265029	.1121426	-11.28	0.000	-1.484825	-1.045234
capexsales	.0491455	.6576897	0.07	0.940	-1.239903	1.338194
grdummy	.1680715	.1375223	1.22	0.222	-.1014673	.4376102
inddis4dmy	-4.76332	.3524054	-13.52	0.000	-5.454022	-4.072618

B4 Density functions for takeover probability

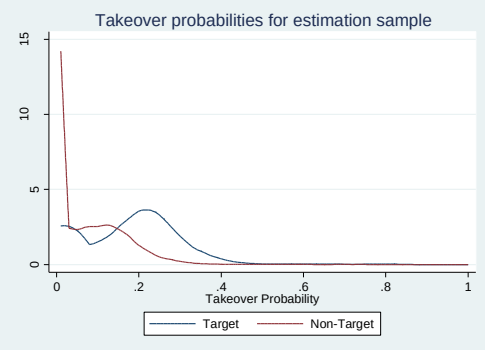
50 estimations



Cutoffs for different regions



UK : 31.0%



Continental Europe: 14.7%

Appendix C: Analyses – Takeover returns

(STATA-File: Deals & CAR_v1.do)

C1 Correlation of takeover probability and CARs

	takeov~b	car50	car20	car10	car5	car501	car201
takeoverprob	1.0000						
car50	0.0983* 0.0403	1.0000					
car20	0.1113* 0.0083	0.8087* 0.0000	1.0000				
car10	0.0212 0.6159	0.6716* 0.0000	0.8314* 0.0000	1.0000			
car5	-0.0057 0.8923	0.5577* 0.0000	0.7446* 0.0000	0.8709* 0.0000	1.0000		
car501	0.0632 0.1182	0.7777* 0.0000	0.5184* 0.0000	0.3779* 0.0000	0.3311* 0.0000	1.0000	
car201	0.0933* 0.0209	0.5798* 0.0000	0.7170* 0.0000	0.4730* 0.0000	0.4079* 0.0000	0.7129* 0.0000	1.0000

C2 Regressions for prediction variables on CAR (STATA-Output)

CAR for [-50, +50]

M1 – Basic model with 4 hypotheses + control for ukdummy

```
. //M1
. regress car50 cagr2  ebitdamargin lneqv pe grdummy ukdummy
```

Source	SS	df	MS		
Model	3.24958194	6	.541596989	Number of obs	= 436
Residual	49.4729547	429	.115321573	F(6, 429)	= 4.70
				Prob > F	= 0.0001
				R-squared	= 0.0616
				Adj R-squared	= 0.0485
Total	52.7225367	435	.121201234	Root MSE	= .33959

car50	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
cagr2	-.0091505	.0507315	-0.18	0.857	-.1088639	.0905628
ebitdamargin	-.1921575	.0825229	-2.33	0.020	-.3543569	-.029958
lneqv	-.0007807	.0101034	-0.08	0.938	-.020639	.0190776
pe	.0007359	.0003927	1.87	0.062	-.0000359	.0015078
grdummy	.0064547	.0409733	0.16	0.875	-.0740787	.086988
ukdummy	.1681501	.0357899	4.70	0.000	.0978048	.2384955
_cons	.146989	.0675468	2.18	0.030	.0142252	.2797528

M2 – Basic model with 4 hypotheses + industrydummy + control for ukdummy

```
. //M2
. regress car50 cagr2  ebitdamargin lneqv pe grdummy inddis4dmy ukdummy
```

Source	SS	df	MS		
Model	3.46160689	7	.494515271	Number of obs =	436
Residual	49.2609298	428	.11509563	F(7, 428) =	4.30
				Prob > F =	0.0001
Total	52.7225367	435	.121201234	R-squared =	0.0657
				Adj R-squared =	0.0504
				Root MSE =	.33926

car50	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
cagr2	-.0078304	.0506912	-0.15	0.877	-.107465	.0918042
ebitdamargin	-.1948854	.0824665	-2.36	0.019	-.3569751	-.0327957
lneqv	-.0001772	.0101033	-0.02	0.986	-.0200355	.019681
pe	.0007531	.0003925	1.92	0.056	-.0000184	.0015246
grdummy	.0093052	.040987	0.23	0.821	-.0712556	.0898659
inddis4dmy	-.0519351	.0382646	-1.36	0.175	-.1271449	.0232748
ukdummy	.1703166	.0357904	4.76	0.000	.0999698	.2406635
_cons	.1537057	.0676618	2.27	0.024	.0207149	.2866964

M3 – Complete Model

```
. //M3
. regress car50 cagr2  ebitdamargin lneqv pe leverage currat capexsales grdummy inddis4dmy ukdummy
```

Source	SS	df	MS		
Model	3.70184817	10	.370184817	Number of obs =	436
Residual	49.0206885	425	.115342796	F(10, 425) =	3.21
				Prob > F =	0.0005
Total	52.7225367	435	.121201234	R-squared =	0.0702
				Adj R-squared =	0.0483
				Root MSE =	.33962

car50	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
cagr2	-.0015696	.0510348	-0.03	0.975	-.1018816	.0987424
ebitdamargin	-.174675	.0859887	-2.03	0.043	-.343691	-.0056589
lneqv	.0018075	.0102997	0.18	0.861	-.0184372	.0220521
pe	.000746	.000393	1.90	0.058	-.0000264	.0015184
leverage	-.0359913	.036198	-0.99	0.321	-.1071406	.035158
currat	.0070367	.0300174	0.23	0.815	-.0519644	.0660377
capexsales	-.0936834	.1441377	-0.65	0.516	-.3769949	.1896282
grdummy	.0055535	.0419331	0.13	0.895	-.0768686	.0879756
inddis4dmy	-.0525309	.0384121	-1.37	0.172	-.1280322	.0229704
ukdummy	.1692527	.0360668	4.69	0.000	.0983612	.2401442
_cons	.1536972	.0828248	1.86	0.064	-.0091	.3164944

CAR for [-20, +20]

M1 – Basic model with 4 hypotheses + control for ukdummy

```
. //M1
. regress car20 cagr2  ebitdamargin lneqv pe grdummy ukdummy
```

Source	SS	df	MS		
Model	1.4538336	6	.2423056	Number of obs =	561
Residual	28.9085332	554	.052181468	F(6, 554) =	4.64
				Prob > F =	0.0001
Total	30.3623668	560	.054218512	R-squared =	0.0479
				Adj R-squared =	0.0376
				Root MSE =	.22843

car20	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
cagr2	-.0296673	.0233199	-1.27	0.204	-.0754736	.016139
ebitdamargin	-.171166	.0535305	-3.20	0.001	-.2763137	-.0660183
lneqv	.0017663	.0061146	0.29	0.773	-.0102443	.013777
pe	.0004326	.0002323	1.86	0.063	-.0000237	.000889
grdummy	.0106377	.0235236	0.45	0.651	-.0355686	.056844
ukdummy	.0908805	.0222718	4.08	0.000	.047133	.1346279
_cons	.1445281	.04071	3.55	0.000	.0645632	.224493

M2 – Basic model with 4 hypotheses + industrydummy + control for ukdummy

```
. //M2
. regress car20 cagr2  ebitdamargin lneqv pe grdummy inddis4dmy ukdummy
```

Source	SS	df	MS		
Model	1.72065474	7	.24580782	Number of obs	561
Residual	28.6417121	553	.051793331	F(7, 553)	4.75
				Prob > F	0.0000
Total	30.3623668	560	.054218512	R-squared	0.0567
				Adj R-squared	0.0447
				Root MSE	.22758

car20	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
cagr2	-.0280554	.0232439	-1.21	0.228	-.0737125	.0176018
ebitdamargin	-.1728397	.0533362	-3.24	0.001	-.277606	-.0680734
lneqv	.0019507	.0060924	0.32	0.749	-.0100163	.0139177
pe	.0004579	.0002317	1.98	0.049	2.76e-06	.0009131
grdummy	.0151305	.0235194	0.64	0.520	-.0310678	.0613287
inddis4dmy	-.0497796	.021932	-2.27	0.024	-.0928598	-.0066994
ukdummy	.0944383	.0222441	4.25	0.000	.0507451	.1381315
_cons	.1526354	.0407153	3.75	0.000	.0726598	.232611

M3 – Complete Model

```
. //M3
. regress car20 cagr2  ebitdamargin lneqv pe leverage currat capexsales grdummy inddis4dmy ukdummy
```

Source	SS	df	MS		
Model	1.83863573	10	.183863573	Number of obs	561
Residual	28.5237311	550	.051861329	F(10, 550)	3.55
				Prob > F	0.0001
Total	30.3623668	560	.054218512	R-squared	0.0606
				Adj R-squared	0.0435
				Root MSE	.22773

car20	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
cagr2	-.0244454	.023419	-1.04	0.297	-.070447	.0215563
ebitdamargin	-.1572891	.0551861	-2.85	0.005	-.2656905	-.0488878
lneqv	.003244	.0061887	0.52	0.600	-.0089124	.0154005
pe	.0004501	.0002321	1.94	0.053	-5.83e-06	.0009061
leverage	.0036024	.0233705	0.15	0.878	-.042304	.0495088
currat	.0131529	.0174741	0.75	0.452	-.0211712	.0474771
capexsales	-.0971937	.0898753	-1.08	0.280	-.2737346	.0793471
grdummy	.0121045	.0238921	0.51	0.613	-.0348264	.0590353
inddis4dmy	-.0488596	.0219887	-2.22	0.027	-.0920517	-.0056675
ukdummy	.0961831	.022367	4.30	0.000	.0522479	.1401182
_cons	.1354724	.0495172	2.74	0.006	.0382063	.2327384

CAR for [-10, +10]

M1 – Basic model with 4 hypotheses + control for ukdummy

```
. //M1
. regress car10 cagr2  ebitdamargin lneqv pe grdummy ukdummy
```

Source	SS	df	MS		
Model	.870659148	6	.145109858	Number of obs	562
Residual	19.8028331	555	.03568078	F(6, 555)	4.07
				Prob > F	0.0005
Total	20.6734922	561	.036851145	R-squared	0.0421
				Adj R-squared	0.0318
				Root MSE	.18889

car10	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
cagr2	-.0164353	.0192808	-0.85	0.394	-.0543075	.021437
ebitdamargin	-.1390782	.044264	-3.14	0.002	-.2260236	-.0521328
lneqv	.0011655	.0050463	0.23	0.817	-.0087466	.0110776
pe	.0004496	.0001921	2.34	0.020	.0000722	.0008269
grdummy	.0088307	.0194441	0.45	0.650	-.0293622	.0470236
ukdummy	.0639231	.0184147	3.47	0.001	.0277521	.1000941
_cons	.1324549	.0335971	3.94	0.000	.0664619	.1984479

M2 – Basic model with 4 hypotheses + industrydummy + control for ukdummy

```
. //M2
. regress car10 cagr2  ebitdamargin lneqv pe grdummy inddis4dmy ukdummy
```

Source	SS	df	MS		
Model	.89361741	7	.12765963	Number of obs	562
Residual	19.7798748	554	.035703745	F(7, 554)	3.58
				Prob > F	0.0009
				R-squared	0.0432
				Adj R-squared	0.0311
Total	20.6734922	561	.036851145	Root MSE	.18895

car10	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
cagr2	-.0159565	.0192963	-0.83	0.409	-.0538593	.0219462
ebitdamargin	-.1395634	.0442824	-3.15	0.002	-.2265453	-.0525815
lneqv	.0012255	.0050484	0.24	0.808	-.0086909	.0111419
pe	.000457	.0001924	2.38	0.018	.0000791	.0008349
grdummy	.0101585	.0195207	0.52	0.603	-.0281851	.0485021
inddis4dmy	-.014598	.0182046	-0.80	0.423	-.0503565	.0211605
ukdummy	.0649613	.018466	3.52	0.000	.0286893	.1012333
_cons	.1347929	.0337341	4.00	0.000	.0685305	.2010554

M3 – Complete Model

```
. //M3
. regress car10 cagr2  ebitdamargin lneqv pe leverage currat capexsales grdummy inddis4dmy ukdummy
```

Source	SS	df	MS		
Model	1.1230673	10	.11230673	Number of obs	562
Residual	19.5504249	551	.035481715	F(10, 551)	3.17
				Prob > F	0.0006
				R-squared	0.0543
				Adj R-squared	0.0372
Total	20.6734922	561	.036851145	Root MSE	.18837

car10	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
cagr2	-.0129241	.0193687	-0.67	0.505	-.0509696	.0251214
ebitdamargin	-.110958	.0456403	-2.43	0.015	-.2006083	-.0213076
lneqv	.0033985	.0051073	0.67	0.506	-.0066337	.0134306
pe	.0004424	.000192	2.30	0.022	.0000653	.0008196
leverage	.0050035	.0193304	0.26	0.796	-.0329669	.0429739
currat	.0323384	.0144405	2.24	0.026	.0039733	.0607035
capexsales	-.0365459	.0743064	-0.49	0.623	-.1825045	.1094127
grdummy	.0023989	.0197589	0.12	0.903	-.036413	.0412109
inddis4dmy	-.0133223	.0181828	-0.73	0.464	-.0490384	.0223939
ukdummy	.0669353	.018498	3.62	0.000	.0306	.1032705
_cons	.0882225	.0408408	2.16	0.031	.0079998	.1684453

CAR for [-5, +5]

M1 – Basic model with 4 hypotheses + control for ukdummy

```
. //M1
. regress car5 cagr2  ebitdamargin lneqv pe grdummy ukdummy
```

Source	SS	df	MS		
Model	.574337786	6	.095722964	Number of obs	562
Residual	14.7169673	555	.026517058	F(6, 555)	3.61
				Prob > F	0.0016
				R-squared	0.0376
				Adj R-squared	0.0272
Total	15.2913051	561	.027257228	Root MSE	.16284

car5	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
cagr2	-.0142298	.0166215	-0.86	0.392	-.0468786	.018419
ebitdamargin	-.1034581	.0381589	-2.71	0.007	-.1784116	-.0285045
lneqv	.0002365	.0043503	0.05	0.957	-.0083084	.0087815
pe	.0003674	.0001656	2.22	0.027	.0000421	.0006927
grdummy	.0199986	.0167623	1.19	0.233	-.0129266	.0529238
ukdummy	.0503762	.0158749	3.17	0.002	.0191941	.0815584
_cons	.1282673	.0289632	4.43	0.000	.0713763	.1851582

M2 – Basic model with 4 hypotheses + industrydummy + control for ukdummy

```
. //M2
. regress car5 cagr2  ebitdamargin lneqv pe grdummy inddis4dmy ukdummy
```

Source	SS	df	MS		
Model	.574628999	7	.082089857	Number of obs	= 562
Residual	14.7166761	554	.026564397	F(7, 554)	= 3.09
				Prob > F	= 0.0033
Total	15.2913051	561	.027257228	R-squared	= 0.0376
				Adj R-squared	= 0.0254
				Root MSE	= .16299

car5	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
cagr2	-.0141759	.0166443	-0.85	0.395	-.0468696	.0185178
ebitdamargin	-.1035127	.0381965	-2.71	0.007	-.1785404	-.028485
lneqv	.0002433	.0043546	0.06	0.955	-.0083103	.0087969
pe	.0003682	.0001659	2.22	0.027	.0000423	.0006942
grdummy	.0201481	.0168379	1.20	0.232	-.0129258	.053222
inddis4dmy	-.0016441	.0157027	-0.10	0.917	-.0324882	.0292
ukdummy	.0504932	.0159282	3.17	0.002	.0192061	.0817802
_cons	.1285306	.029098	4.42	0.000	.0713748	.1856864

M3 – Complete Model

```
. //M3
. regress car5 cagr2  ebitdamargin lneqv pe leverage currat capexsales grdummy inddis4dmy ukdummy
```

Source	SS	df	MS		
Model	.711980061	10	.071198006	Number of obs	= 562
Residual	14.5793251	551	.026459755	F(10, 551)	= 2.69
				Prob > F	= 0.0032
Total	15.2913051	561	.027257228	R-squared	= 0.0466
				Adj R-squared	= 0.0293
				Root MSE	= .16266

car5	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
cagr2	-.011178	.0167259	-0.67	0.504	-.0440324	.0216764
ebitdamargin	-.0837287	.039413	-2.12	0.034	-.1611468	-.0063106
lneqv	.0018098	.0044104	0.41	0.682	-.0068535	.0104731
pe	.0003596	.0001658	2.17	0.031	.000034	.0006853
leverage	.0087324	.0166929	0.52	0.601	-.0240571	.041522
currat	.0216512	.0124702	1.74	0.083	-.0028437	.0461461
capexsales	-.0667354	.0641678	-1.04	0.299	-.1927788	.0593081
grdummy	.0151294	.0170629	0.89	0.376	-.0183869	.0486458
inddis4dmy	-.0003746	.0157019	-0.02	0.981	-.0312175	.0304682
ukdummy	.0526331	.0159741	3.29	0.001	.0212556	.0840106
_cons	.0971538	.0352683	2.75	0.006	.027877	.1664306

CAR for [-50, -1]

M1 – Basic model with 4 hypotheses + control for ukdummy

```
. regress car501 cagr2  ebitdamargin lneqv pe grdummy ukdummy
```

Source	SS	df	MS		
Model	.836003598	6	.139333933	Number of obs	= 613
Residual	41.961558	606	.069243495	F(6, 606)	= 2.01
				Prob > F	= 0.0621
Total	42.7975616	612	.069930656	R-squared	= 0.0195
				Adj R-squared	= 0.0098
				Root MSE	= .26314

car501	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
cagr2	.0229027	.0266346	0.86	0.390	-.0294046	.0752101
ebitdamargin	-.0559662	.0600006	-0.93	0.351	-.1738006	.0618683
lneqv	.0109956	.006725	1.64	0.103	-.0022116	.0242028
pe	.0003418	.0002638	1.30	0.196	-.0001762	.0008599
grdummy	-.0274165	.0256586	-1.07	0.286	-.077807	.022974
ukdummy	.0606667	.023335	2.60	0.010	.0148394	.106494
_cons	.0008215	.04364	0.02	0.985	-.0848826	.0865255

M2 – Basic model with 4 hypotheses + industrydummy + control for ukdummy

```
. //M2
. regress car501 cagr2  ebitdamargin lneqv pe grdummy inddis4dmy ukdummy
```

Source	SS	df	MS		
Model	1.04396899	7	.149138427	Number of obs	613
Residual	41.7535926	605	.069014203	F(7, 605)	2.16
				Prob > F	0.0360
Total	42.7975616	612	.069930656	R-squared	0.0244
				Adj R-squared	0.0131
				Root MSE	.26271

car501	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
cagr2	.0244504	.0266054	0.92	0.358	-.0277998	.0767005
ebitdamargin	-.057501	.0599077	-0.96	0.338	-.1751534	.0601514
lneqv	.0112267	.0067152	1.67	0.095	-.0019613	.0244146
pe	.0003622	.0002636	1.37	0.170	-.0001555	.0008799
grdummy	-.024423	.025674	-0.95	0.342	-.074844	.025998
inddis4dmy	-.0422249	.0243244	-1.74	0.083	-.0899955	.0055456
ukdummy	.0636831	.0233611	2.73	0.007	.0178045	.1095618
_cons	.0074267	.0437336	0.17	0.865	-.0784613	.0933147

M3 – Complete Model

```
. //M3
. regress car501 cagr2  ebitdamargin lneqv pe leverage currat capexsales grdummy inddis4dmy ukd
> ummy
```

Source	SS	df	MS		
Model	1.83841298	10	.183841298	Number of obs	613
Residual	40.9591486	602	.068038453	F(10, 602)	2.70
				Prob > F	0.0030
Total	42.7975616	612	.069930656	R-squared	0.0430
				Adj R-squared	0.0271
				Root MSE	.26084

car501	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
cagr2	.027981	.0265994	1.05	0.293	-.0242579	.08022
ebitdamargin	-.0209762	.061157	-0.34	0.732	-.1410833	.0991308
lneqv	.0139052	.0067591	2.06	0.040	.0006309	.0271795
pe	.0003132	.0002621	1.19	0.233	-.0002016	.000828
leverage	-.0639912	.0261319	-2.45	0.015	-.115312	-.0126704
currat	.0263838	.0186888	1.41	0.159	-.0103195	.063087
capexsales	.0713065	.0987645	0.72	0.471	-.1226584	.2652714
grdummy	-.0354343	.0260849	-1.36	0.175	-.0866627	.0157942
inddis4dmy	-.0444455	.0242157	-1.84	0.067	-.0920031	.003112
ukdummy	.0617047	.0233032	2.65	0.008	.0159393	.10747
_cons	-.0176724	.0531452	-0.33	0.740	-.122045	.0867002

CAR for [-20, -1]

M1 – Basic model with 4 hypotheses + control for ukdummy

```
. regress car201 cagr2  ebitdamargin lneqv pe grdummy ukdummy

      Source |       SS       df       MS              Number of obs =     613
-------------+------------------------------           F(  6,   606) =    2.67
       Model |  .395056941     6  .065842823            Prob > F      =  0.0147
    Residual |  14.9717914   606  .024705926            R-squared     =  0.0257
-------------+------------------------------           Adj R-squared =  0.0161
       Total |  15.3668483   612  .025109229            Root MSE      =  .15718

------------------------------------------------------------------------------
      car201 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       cagr2 |  -.0058836   .0159095    -0.37   0.712    -.0371281    .0253609
ebitdamargin |  -.1105102   .0358399    -3.08   0.002    -.1808958   -.0401247
       lneqv |   .0069887    .004017     1.74   0.082    -.0009003    .0148776
          pe |   .0001489   .0001576     0.95   0.345    -.0001605    .0004584
     grdummy |  -.0006705   .0153265    -0.04   0.965      -.03077    .0294291
     ukdummy |    .039384   .0139386     2.83   0.005     .0120101    .0667578
       _cons |    .025694   .0260673     0.99   0.325    -.0254993    .0768872
------------------------------------------------------------------------------
```

M2 – Basic model with 4 hypotheses + industrydummy + control for ukdummy

```
. regress car201 cagr2  ebitdamargin lneqv pe grdummy inddis4dmy ukdummy

      Source |       SS       df       MS              Number of obs =     613
-------------+------------------------------           F(  7,   605) =    3.03
       Model |  .521054116     7  .074436302            Prob > F      =  0.0038
    Residual |  14.8457942   605  .024538503            R-squared     =  0.0339
-------------+------------------------------           Adj R-squared =  0.0227
       Total |  15.3668483   612  .025109229            Root MSE      =  .15665

------------------------------------------------------------------------------
      car201 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       cagr2 |   -.004679   .0158644    -0.29   0.768     -.035835    .0264771
ebitdamargin |  -.1117049   .0357222    -3.13   0.002    -.1818594   -.0415504
       lneqv |   .0071685   .0040042     1.79   0.074    -.0006953    .0150323
          pe |   .0001648   .0001572     1.05   0.295    -.0001439    .0004735
     grdummy |   .0016596   .0153091     0.11   0.914    -.0284058     .031725
   inddis4dmy |  -.0328665   .0145043    -2.27   0.024    -.0613515   -.0043816
     ukdummy |   .0417318   .0139299     3.00   0.003      .014375    .0690886
       _cons |   .0308353   .0260777     1.18   0.237    -.0203786    .0820491
------------------------------------------------------------------------------
```

M3 – Complete Model

```
. regress car201 cagr2  ebitdamargin lneqv pe leverage currat capexsales grdummy inddis4dmy ukd
> ummy

      Source |       SS       df       MS              Number of obs =     613
-------------+------------------------------           F( 10,   602) =    2.62
       Model |  .640930026    10  .064093003            Prob > F      =  0.0040
    Residual |  14.7259183   602  .024461658            R-squared     =  0.0417
-------------+------------------------------           Adj R-squared =  0.0258
       Total |  15.3668483   612  .025109229            Root MSE      =   .1564

------------------------------------------------------------------------------
      car201 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       cagr2 |  -.0017393   .0159492    -0.11   0.913    -.0330621    .0295835
ebitdamargin |  -.0963105   .0366701    -2.63   0.009    -.1683273   -.0242936
       lneqv |   .0082048   .0040528     2.02   0.043     .0002455    .0161642
          pe |   .0001479   .0001572     0.94   0.347    -.0001608    .0004566
    leverage |  -.0246779   .0156689    -1.57   0.116    -.0554501    .0060944
      currat |   .0069339   .0112059     0.62   0.536    -.0150736    .0289414
  capexsales |  -.0324792   .0592198    -0.55   0.584    -.1487816    .0838233
     grdummy |  -.0018216   .0156407    -0.12   0.907    -.0325385    .0288953
   inddis4dmy |  -.0338049   .0145199    -2.33   0.020    -.0623207   -.0052892
     ukdummy |   .0411663   .0139727     2.95   0.003     .0137252    .0686075
       _cons |   .0281247   .0318662     0.88   0.378    -.0344577    .0907071
------------------------------------------------------------------------------
```

Appendix D: Prediction & Out-of-sample tests

(STATA-File: Investment_test_v2.do)

D1 Sample composition (STATA-Output)

-> after elimination of missing stock returns (18 observations)

targetdummy	year 2011	2012	Total
0	1,723	1,677	3,400
1	49	21	70
Total	1,772	1,698	3,470

targetdummy	country CH	DE	FR	SE	UK	Total
0	282	812	725	348	1,233	3,400
1	4	10	19	5	32	70
Total	286	822	744	353	1,265	3,470

D2 Descriptive statistics (STATA-Output)

-> after elimination of missing stock returns

```
. summarize cagr1 cagr2 ebitdamargin roe assetturn lntotass lnsales lneqv pe mb g
> rdummy leverage liquidity currat capexsales inddis4dmy if targetdummy==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
cagr1	3400	.1684723	.8613795	-.704263	36.0811
cagr2	3400	.0788588	.5681309	-.672538	20.1081
ebitdamargin	3400	.1159822	.2835803	-7.45204	1.10082
roe	3400	.0787416	.4462739	-4.35345	9.21837
assetturn	3400	1.126856	.7276843	.006879	8.06286
lntotass	3400	5.93009	2.114503	1.108992	12.7029
lnsales	3400	5.858838	2.093857	1.613689	12.83606
lneqv	3400	5.546961	2.101298	2.305511	12.24821
pe	3400	15.06942	41.11742	-193.623	461.313
mb	3400	.9755395	1.047012	.00831	17.618
grdummy	3400	.25	.4330764	0	1
leverage	3400	.2863953	.389629	0	5.941261
liquidity	3400	.1479211	.1467309	0	.95044
currat	3400	1.862624	1.480779	.077716	19.7047
capexsales	3400	.052963	.0911835	0	.94873
inddis4dmy	3400	.4052941	.4910211	0	1

```
. summarize cagr1 cagr2 ebitdamargin roe assetturn lntotass lnsales lneqv pe mb g
> rdummy leverage liquidity currat capexsales inddis4dmy if targetdummy==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
cagr1	70	.0642715	.2148771	-.527036	.850251
cagr2	70	.0451413	.1765951	-.293098	.511609
ebitdamargin	70	.1105284	.1374527	-.256635	.838511
roe	70	.0087208	.5842383	-3.76974	2.06754
assetturn	70	1.143198	.7150873	.09848	4.5498
lntotass	70	5.372494	1.537682	2.518502	8.88141
lnsales	70	5.330747	1.565597	2.402068	8.933045
lneqv	70	5.17472	1.612982	2.372484	9.234809
pe	70	11.89639	32.12743	-133.828	81.7871
mb	70	1.091787	.84876	.108427	5.17913
grdummy	70	.2285714	.4229444	0	1
leverage	70	.2396982	.2960556	.0001392	1.596889
liquidity	70	.1511064	.1148267	.012479	.630607
currat	70	1.094728	.8501883	.131697	6.10779
capexsales	70	.0355046	.0628723	.002385	.435677
inddis4dmy	70	.2428571	.4319056	0	1

D3 Takeover probability – Descriptive statistics

Descriptive statistics of the takeover probabilities for the hold-out sample can be found on the attached CD-ROM due to limited space.

D4 Prediction accuracy and investment test for various scenarios (STATA Output)

1) ALL

Variable	Obs	Mean	Std. Dev.	Min	Max
takeoverprob	3400	.1087238	.1418249	2.42e-12	.8330281

```
. summarize takeoverprob if targetdummy==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
takeoverprob	70	.2306742	.192101	.0001335	.6532583

targetdummy	targetexp 0	1	Total
0	2,583 98.78	817 95.56	3,400 97.98
1	32 1.22	38 4.44	70 2.02
Total	2,615 100.00	855 100.00	3,470 100.00

targetdummy	takeoverprob10					
	0	1	2	3	4	Total
0	344	345	346	341	340	3,400
	99.14	99.42	99.71	98.27	97.98	97.98
1	3	2	1	6	7	70
	0.86	0.58	0.29	1.73	2.02	2.02
Total	347	347	347	347	347	3,470
	100.00	100.00	100.00	100.00	100.00	100.00

targetdummy	takeoverprob10					
	5	6	7	8	9	Total
0	347	339	339	332	327	3,400
	100.00	97.69	97.69	95.68	94.24	97.98
1	0	8	8	15	20	70
	0.00	2.31	2.31	4.32	5.76	2.02
Total	347	347	347	347	347	3,470
	100.00	100.00	100.00	100.00	100.00	100.00

```
. sum yearreturn if targetdummy==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
yearreturn	70	.3889795	.5208315	-.9175552	2.003891

```
. sum yearreturn if targetdummy==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
yearreturn	3400	-.0090954	.4014034	-.9939824	5.036513

takeoverprob10	N	mean	p50	sd	min	max
0	347	-.0176172	-.0562584	.5020368	-.8830972	5.036513
1	347	.0267407	-.0049684	.4049496	-.9303797	1.875
2	347	-.0125445	-.0286275	.351888	-.9844311	1.981367
3	347	.035434	.0077793	.4230108	-.9844156	2.840741
4	347	.0617331	.0128898	.4122892	-.8635885	2.253012
5	347	-.0295838	-.0660211	.3753371	-.9095879	3.074519
6	347	-.0371266	-.0625	.37318	-.9168355	2.105077
7	347	-.0272401	-.0449569	.3689373	-.9352941	1.813559
8	347	.0093305	-.0071942	.4070268	-.9939824	1.636535
9	347	-.0197764	-.0489378	.4334879	-.9922619	1.948025
Total	3470	-.001065	-.0280576	.4079241	-.9939824	5.036513

2) All 2011

Variable	Obs	Mean	Std. Dev.	Min	Max
takeoverprob	1723	.1170891	.1472574	2.42e-12	.6731035

```
. summarize takeoverprob if targetdummy==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
takeoverprob	49	.2114308	.1803435	.0001335	.6532583

targetdummy	targetexp 0	1	Total
0	1,273 98.07	450 94.94	1,723 97.23
1	25 1.93	24 5.06	49 2.77
Total	1,298 100.00	474 100.00	1,772 100.00

targetdummy	takeoverprob10 0	1	2	3	4	Total
0	174 98.31	175 98.87	175 98.87	173 97.74	176 98.88	1,723 97.23
1	3 1.69	2 1.13	2 1.13	4 2.26	2 1.12	49 2.77
Total	177 100.00	177 100.00	177 100.00	177 100.00	178 100.00	1,772 100.00

targetdummy	takeoverprob10 5	6	7	8	9	Total
0	176 99.44	169 95.48	173 97.74	163 92.09	169 94.94	1,723 97.23
1	1 0.56	8 4.52	4 2.26	14 7.91	9 5.06	49 2.77
Total	177 100.00	177 100.00	177 100.00	177 100.00	178 100.00	1,772 100.00

Variable	Obs	Mean	Std. Dev.	Min	Max
yearreturn	49	.3528079	.5555959	-.9175552	2.003891

```
. sum yearreturn if targetdummy==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
yearreturn	1723	-.1413514	.3559137	-.9939824	5.036513

takeoverprob10	N	mean	p50	sd	min	max
0	177	-.1445865	-.1821632	.5270627	-.8830972	5.036513
1	177	-.1234245	-.1414554	.3549967	-.9303797	1.524612
2	177	-.1616459	-.1764392	.3151228	-.9844311	.9253651
3	177	-.0684836	-.0933852	.3569138	-.8635885	1.393939
4	178	-.0996233	-.1332904	.3332358	-.8	2
5	177	-.1513225	-.1782407	.2896406	-.9095879	.9904838
6	177	-.1523142	-.1916859	.3583519	-.8126761	2.003891
7	177	-.075016	-.1	.3658565	-.9352941	1.813559
8	177	-.1107519	-.1395003	.4004265	-.9939824	1.633028
9	178	-.1895079	-.1925807	.355504	-.9914644	.9723215
Total	1772	-.1276867	-.1539472	.3716257	-.9939824	5.036513

3) All 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
takeoverprob	1677	.1001291	.1355245	3.64e-11	.8330281

```
. summarize takeoverprob if targetdummy==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
takeoverprob	21	.2755756	.2150197	.0023295	.6531484

targetdummy	targetexp 0	1	Total
0	1,310 99.47	367 96.33	1,677 98.76
1	7 0.53	14 3.67	21 1.24
Total	1,317 100.00	381 100.00	1,698 100.00

targetdummy	takeoverprob10 0	1	2	3	4	Total
0	169 100.00	170 100.00	170 100.00	168 98.82	166 97.65	1,677 98.76
1	0 0.00	0 0.00	0 0.00	2 1.18	4 2.35	21 1.24
Total	169 100.00	170 100.00	170 100.00	170 100.00	170 100.00	1,698 100.00

targetdummy	takeoverprob10 5	6	7	8	9	Total
0	169 100.00	170 100.00	169 99.41	166 97.65	160 94.12	1,677 98.76
1	0 0.00	0 0.00	1 0.59	4 2.35	10 5.88	21 1.24
Total	169 100.00	170 100.00	170 100.00	170 100.00	170 100.00	1,698 100.00

Variable	Obs	Mean	Std. Dev.	Min	Max
yearreturn	21	.4733801	.4293394	-.8823529	1.179989

```
. sum yearreturn if targetdummy==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
yearreturn	1677	.1267884	.4001986	-.9922619	3.074519

takeoverprob10	N	mean	p50	sd	min	max
0	169	.1154821	.0526316	.4396052	-.7454545	3.067039
1	170	.1602297	.1235385	.3791397	-.7130114	1.406618
2	170	.1210846	.0897895	.3756432	-.7916667	1.981367
3	170	.1430831	.1073826	.438478	-.891997	2.840741
4	170	.1917042	.1314969	.4344707	-.8030303	2.253012
5	169	.1090779	.0563287	.3915538	-.8067881	3.074519
6	170	.076798	.0805517	.3775654	-.9168355	2.105077
7	170	.0865147	.0820254	.3483406	-.7321429	1.170732
8	170	.116634	.1047236	.3904969	-.9335938	1.636535
9	170	.1899194	.1738978	.4288542	-.9922619	1.948025
Total	1698	.1310749	.096862	.4022655	-.9922619	3.074519

4) UK 2011

Variable	Obs	Mean	Std. Dev.	Min	Max
takeoverprob	609	.1890143	.19502	2.66e-09	.6731035

. summarize takeoverprob if targetdummy==1

Variable	Obs	Mean	Std. Dev.	Min	Max
takeoverprob	16	.3122536	.2419379	.0034335	.6532583

targetdummy	targetexp 0	1	Total
0	320 98.46	289 96.33	609 97.44
1	5 1.54	11 3.67	16 2.56
Total	325 100.00	300 100.00	625 100.00

18%cutoff

targetdummy	targetexp 0	1	Total
0	422 98.37	187 95.41	609 97.44
1	7 1.63	9 4.59	16 2.56
Total	429 100.00	196 100.00	625 100.00

31% cutoff (UK)

targetdummy	takeoverprob10 0	1	2	3	4	Total
0	62 100.00	63 100.00	60 96.77	61 96.83	61 98.39	609 97.44
1	0 0.00	0 0.00	2 3.23	2 3.17	1 1.61	16 2.56
Total	62 100.00	63 100.00	62 100.00	63 100.00	62 100.00	625 100.00

targetdummy	takeoverprob10 5	6	7	8	9	Total
0	62 98.41	60 96.77	62 98.41	59 95.16	59 93.65	609 97.44
1	1 1.59	2 3.23	1 1.59	3 4.84	4 6.35	16 2.56
Total	63 100.00	62 100.00	63 100.00	62 100.00	63 100.00	625 100.00

Variable	Obs	Mean	Std. Dev.	Min	Max
yearreturn	16	.467285	.4536466	-.3146853	1.382023

. sum yearreturn if targetdummy==0

Variable	Obs	Mean	Std. Dev.	Min	Max
yearreturn	609	-.1082107	.3680484	-.9939824	2

takeoverprob10	N	mean	p50	sd	min	max
0	62	-.1830812	-.2037537	.3777139	-.9303797	.9282297
1	63	-.052075	-.1017609	.323057	-.8007836	.8068182
2	62	-.0540083	-.0694552	.3423389	-.858209	.8269231
3	63	-.0176137	-.0280778	.3879446	-.8	1.393939
4	62	-.0728335	-.0716449	.4071597	-.7027027	2
5	63	.0178332	-.063253	.4312998	-.9352941	1.813559
6	62	-.06066	-.0613789	.402765	-.9939824	1.382023
7	63	-.1186517	-.1656977	.3345225	-.8356522	.9503546
8	62	-.2116616	-.2037459	.3437155	-.9914644	.6982759
9	63	-.1838512	-.2109164	.3998273	-.9763314	.9723215
Total	625	-.093478	-.1165049	.3810618	-.9939824	2

5) UK 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
takeoverprob	624	.1602027	.1810748	3.64e-11	.8330281

```
. summarize takeoverprob if targetdummy==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
takeoverprob	16	.3235216	.2190894	.0071239	.6531484

targetdummy	targetexp 0	1	Total
0	367 98.92	257 95.54	624 97.50
1	4 1.08	12 4.46	16 2.50
Total	371 100.00	269 100.00	640 100.00

18%cutoff

targetdummy	targetexp 0	1	Total
0	470 98.74	154 93.90	624 97.50
1	6 1.26	10 6.10	16 2.50
Total	476 100.00	164 100.00	640 100.00

31% cutoff (UK)

targetdummy	takeoverprob10 0	1	2	3	4	Total
0	64 100.00	64 100.00	64 100.00	63 98.44	61 95.31	624 97.50
1	0 0.00	0 0.00	0 0.00	1 1.56	3 4.69	16 2.50
Total	64 100.00	64 100.00	64 100.00	64 100.00	64 100.00	640 100.00

targetdummy	takeoverprob10 5	6	7	8	9	Total
0	62 96.88	64 100.00	64 100.00	60 93.75	58 90.63	624 97.50
1	2 3.13	0 0.00	0 0.00	4 6.25	6 9.38	16 2.50
Total	64 100.00	64 100.00	64 100.00	64 100.00	64 100.00	640 100.00

Variable	Obs	Mean	Std. Dev.	Min	Max
yearreturn	16	.4484031	.4894887	-.8823529	1.179989

```
. sum yearreturn if targetdummy==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
yearreturn	624	.1891884	.4665564	-.9922619	3.067039

by categories of: takeoverprob10

takeoverprob10	N	mean	p50	sd	min	max
0	64	.1284337	.0290122	.5916212	-.7454545	3.067039
1	64	.185476	.09653	.508905	-.7916667	1.981367
2	64	.1836549	.152811	.4729068	-.8809524	2.840741
3	64	.1719388	.169629	.3763461	-.6850393	1.436709
4	64	.3800304	.315945	.5775827	-.8030303	2.253012
5	64	.1377523	.148979	.3834174	-.7321429	1.170732
6	64	.1690958	.1296197	.4526897	-.9335938	1.636535
7	64	.2268795	.1979277	.4100998	-.9922619	1.437158
8	64	.2169639	.173907	.4084632	-.6201005	1.948025
9	64	.1564627	.1589974	.4293327	-.8823529	1.179989
Total	640	.1956688	.1563917	.4684968	-.9922619	3.067039

6) CE 2011

Variable	Obs	Mean	Std. Dev.	Min	Max
takeoverprob	1114	.0777691	.0916278	2.42e-12	.6097423

```
. summarize takeoverprob if targetdummy==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
takeoverprob	33	.162547	.1174774	.0001335	.4302326

targetdummy	targetexp 0	1	Total
0	953 97.94	161 92.53	1,114 97.12
1	20 2.06	13 7.47	33 2.88
Total	973 100.00	174 100.00	1,147 100.00

18%

targetdummy	targetexp 0	1	Total
0	860 98.29	254 93.38	1,114 97.12
1	15 1.71	18 6.62	33 2.88
Total	875 100.00	272 100.00	1,147 100.00

14.7%

targetdummy	takeoverprob10					
	0	1	2	3	4	Total
0	113	111	115	112	114	1,114
	99.12	96.52	100.00	98.25	99.13	97.12
1	1	4	0	2	1	33
	0.88	3.48	0.00	1.75	0.87	2.88
Total	114	115	115	114	115	1,147
	100.00	100.00	100.00	100.00	100.00	100.00

targetdummy	takeoverprob10					
	5	6	7	8	9	Total
0	115	110	110	111	103	1,114
	100.00	96.49	95.65	96.52	89.57	97.12
1	0	4	5	4	12	33
	0.00	3.51	4.35	3.48	10.43	2.88
Total	115	114	115	115	115	1,147
	100.00	100.00	100.00	100.00	100.00	100.00

Variable	Obs	Mean	Std. Dev.	Min	Max
yearreturn	33	.2973038	.597356	-.9175552	2.003891

```
. sum yearreturn if targetdummy==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
yearreturn	1114	-.1594687	.3479365	-.9844311	5.036513

takeoverprob10	N	mean	p50	sd	min	max
0	114	-.1451946	-.1810498	.5975866	-.8830972	5.036513
1	115	-.0715049	-.0878737	.3766688	-.8044872	1.524612
2	115	-.1822809	-.2071429	.2834392	-.8322026	.9253651
3	114	-.1875201	-.2105261	.3492306	-.9844311	.858736
4	115	-.1304232	-.1431071	.2715834	-.8635885	.7274194
5	115	-.1726935	-.192	.2771397	-.9095879	1.079379
6	114	-.1174028	-.1552672	.3424168	-.7393745	2.003891
7	115	-.1691095	-.2156609	.3400596	-.8126761	1.510726
8	115	-.1264955	-.1305395	.3118189	-.6921739	1.471722
9	115	-.1607422	-.1765734	.3904266	-.9374996	1.633028
Total	1147	-.146327	-.1703281	.3652025	-.9844311	5.036513

7) CE 2012

Variable	Obs	Mean	Std. Dev.	Min	Max
takeoverprob	1053	.0645299	.0802182	4.77e-11	.6901327

```
. summarize takeoverprob if targetdummy==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
takeoverprob	5	.1221485	.112011	.0023295	.2219328

targetdummy	targetexp 0	1	Total
0	943 99.68	110 98.21	1,053 99.53
1	3 0.32	2 1.79	5 0.47
Total	946 100.00	112 100.00	1,058 100.00

18%

targetdummy	targetexp 0	1	Total
0	866 99.77	187 98.42	1,053 99.53
1	2 0.23	3 1.58	5 0.47
Total	868 100.00	190 100.00	1,058 100.00

14.7%

targetdummy	takeoverprob10 0	1	2	3	4	Total
0	105 100.00	106 100.00	106 100.00	106 100.00	104 98.11	1,053 99.53
1	0 0.00	0 0.00	0 0.00	0 0.00	2 1.89	5 0.47
Total	105 100.00	106 100.00	106 100.00	106 100.00	106 100.00	1,058 100.00

targetdummy	takeoverprob10 5	6	7	8	9	Total
0	105 100.00	106 100.00	106 100.00	105 99.06	104 98.11	1,053 99.53
1	0 0.00	0 0.00	0 0.00	1 0.94	2 1.89	5 0.47
Total	105 100.00	106 100.00	106 100.00	106 100.00	106 100.00	1,058 100.00

Variable	Obs	Mean	Std. Dev.	Min	Max
yearreturn	5	.5533064	.1126223	.4469453	.7356688

```
. sum yearreturn if targetdummy==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
yearreturn	1053	.0898106	.3501023	-.9168355	3.074519

takeoverprob10	N	mean	p50	sd	min	max
0	105	.1032811	.0648836	.3176531	-.6833134	1.284972
1	106	.1642081	.143717	.3627122	-.7130114	1.406618
2	106	.1286505	.0784233	.3486668	-.6389797	1.272727
3	106	.0931753	.0897895	.2880451	-.7890909	.7488263
4	106	.0733654	.042827	.3826854	-.891997	1.780619
5	105	.1178327	.0658415	.3988423	-.8067881	3.074519
6	106	.0794165	.0587841	.3568984	-.8343108	1.587102
7	106	.0497901	.0297873	.3623016	-.9168355	2.105077
8	106	.0902452	.0904001	.360034	-.6197674	1.142132
9	106	.0203957	.0203087	.3090291	-.7777778	.8075331
Total	1058	.0920011	.0669459	.3507866	-.9168355	3.074519

Appendix E: In-sample investment test

(STATA-File: Investment_test_estimation_v2.do)

The individual outputs for the test of investment returns for the estimation sample can be found on the attached CD-ROM due to limited space.

Declaration of Authorship

" I hereby declare

- that I have written this thesis without any help from others and without the use of documents and aids other than those stated above,
- that I have mentioned all used sources and that I have cited them correctly according to established academic citation rules."

_____

Hendrik Froese

St. Gallen, 17th of May 2013