Stockholm School of Economics

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Do LBO Motives Differ Between Large and Small Firms?

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Takeover prediction modeling of UK takeover offers 1998-2008

Abstract: Authors of previous takeover prediction models treat small and large takeover targets as one homogenous group. Our empirical results show that treating large and small LBOs as one homogenous group leads to misleading takeover prediction results and low prediction power. We find that small public-to-private LBO transactions are mainly driven by undervaluation of the target while large public-to-private LBO transactions are driven by potential to increase efficiency as well as transfer wealth from limited partners to general partners. Since the motives for large and small differ, prediction of small and large public-to-private LBO transactions cannot be achieved with one model. We show that separating small and large LBOs increases prediction accuracy from 46% to 74% and 70% respectively. A direct implication of this would be higher abnormal returns earned from an investment trading strategy based on stock-picking takeover targets in advance.

Keywords: Takeover prediction, public-to-private, leveraged buyouts, private equity

Authors: Keiward Pham (21259) ♣ and Kristina Saudargaite (40339)♦

Tutor: Håkan Thorsell

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♣keiward.pham@alumni.hhs.se

♦kristina.saudargaite@alumni.hhs.se

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1 Introduction

In this section we give the reader background of our research topic, purpose, and the main contribution to the existing literature.

1.1 Background

Franks and Harris (1989) have showed that the stock price of a takeover target tend to increase after the announcement of the bid, averaging returns of around 30% (premium level in relation to the pre-announcement stock price). Hence, a public-to-private takeover prediction model that enables stock-picking of likely takeover targets in advance could potentially be a successful trading strategy on the stock market. Moreover, better understanding of the underlying motives for public-to-private takeover activity can be interesting in itself. For example, expropriations of value on behalf of minority shareholders could be important in a regulative context for policy makers.

Despite the potential currently existing takeover prediction models have poor prediction power. Although some authors in the earlier studies claim prediction power higher than 70%, Palepu (1986) criticizes that they did not account for several methodological flaws. Authors making prediction models after Palepu's (1986) criticism, made recommended adjustments which resulted in more moderate results of prediction power.

To construct a takeover prediction model, we need to understand the underlying motives driving these transactions. We hypothesize that the firm characteristics for smaller takeover firms differ from large takeovers due to different takeover motives. Renneboog and Simons (2005) show that the motives depend on the size of the target. For example, large companies are more likely to be taken over in order to change management that engages in empire building while small companies are more likely to be taken over for buy-and-build strategy. However, currently existing takeover prediction models ignore these differences and treat small and large takeover targets as one homogenous group. Hence, we believe that the prediction power could be improved when large and small takeovers are accounted for separately.

1.2 Purpose

We contribute to the existing literature by size-tailoring takeover prediction models into large and small firms and as a result using financial ratios that better reflect motives for takeover. Thus, we expect these models to have higher explanatory power and provide better foundation for stock-picking potential takeover targets as an investment strategy. The firm characteristics of the takeover targets are potential determinants of the underlying motives driving the takeovers. Thus, size-tailoring takeover prediction models also gives us better understanding whether the takeover motives for large and small firms differ.

Hence, our two inter-related research questions are:

Research question 1: Does the prediction power of a takeover prediction model improve when we separate the sample into large and small firms?

Research question 2: Do underlying motives that drive LBOs differ between small and large firms?

1.3 Main Findings

We find that the characteristics of large and small takeover targets differ significantly. When size-tailoring our prediction models the prediction power improves from 46% to 74% for the small companies and to 70% for the large companies. We draw the conclusion that treating large and small firms as one homogenous group will likely lead to higher misclassifications which would affect the outcome of using takeover prediction models as an investment trading strategy.

We also find that the motives behind small and large takeovers differ. The main motive for small takeovers is mainly related to value transfer from pre-transactional shareholders, i.e. undervalued firms are taken over. On the other hand, large takeovers are driven by both value creation and value transfer motives. Large inefficient firms are more likely to receive a takeover bid. This shows that buyers are looking for potential to create value. At the same time, large firms with high operating risk are more likely to receive a takeover bid. This supports the hypothesis that so far has not been included in the takeover prediction models, namely the wealth transfer motive from limited partners (LPs)[2] to general partners (GPs)[3] in a private equity firm.

[2]General Partners are active in the private equity firm's day-to-day operations and are the decision-makers of the investments made by the fund.

[3]Limited Partners to a private equity firm are the investors and fund providers and do neither have any management responsibility nor decision rights in the investments (hence the limited partnership).

2 Definitions and Delimitations

In this section we define terms used in this thesis and explain delimitations of our research.

Takeover is defined as *takeover offer* rather than successfully *completed deal*. All of the previous authors of takeover prediction models in the USA and Europe defined *targets* as successfully completed deals. Hyde (2009), however, took a different approach. In his paper *Predicting Takeover Offers in Australia*, he included both successful and unsuccessful bids. Stock prices increase already on the announcement day of a takeover bid irrespectively whether the bid is successfully completed. Since potential application of our prediction model is stock-picking for the earlier explained trading strategy, excluding unsuccessful bids would reduce the opportunity to earn abnormal returns; thus, in practice predicting takeover offers is better than predicting takeovers. Following Hyde's (2009) logic and thinking about potential application of our prediction model, we make takeover offer prediction model rather than takeover prediction model.

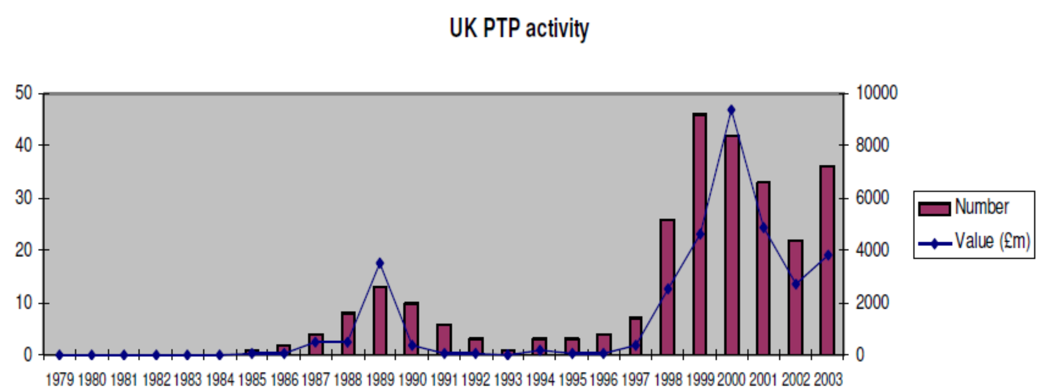
Leveraged buyout (LBO) is defined as gaining controlling interest in a firm and using borrowed capital to partially finance the acquisition. In this thesis terms t*akeover* and *leverage buyout (LBO)* are used interchangeably and the definition of LBO is *public-to-private LBO offers by private equity firms.*

- We are looking only at *public-to-private* LBOs because the practical application of our prediction model requires stock of the target firm to be publicly traded. Since we aim to construct takeover prediction model that enables stock-picking of likely targets, predicting private-to-private LBOs would not serve the purpose.
- Secondly, we are looking only at public-to-private LBOs where the acquirer is a *private equity firm* because the motives behind strategic LBOs differ. The strategic rationale is not captured in the accounting data of a target firm. Although strategic rationale could be captured by looking at the accounting data of both target firm and acquiring firm, an investor who uses takeover prediction model does not know who will be the acquirer. Thus, in order to make a takeover prediction model that could be used for building a trading strategy, we cannot use accounting data of the acquiring firm. This naturally limits us to private equity buyers. On the broader

note, finding empirical support what motives drive LBO transactions by private equity firms is interesting in itself because of the controversy of these transactions.

Finally, we limit our study to the manufacturing firms in the UK during the period 1998-2008. We limit our research to manufacturing firms because we want to eliminate variation in the accounting ratios across industries. The main reason why we study LBOs of the firms listed in the UK is the lack of the existing research on public-to-private transactions in the UK during 1998-2008. As pointed out by Renneboog & Simons (2005), despite economically significant development of public-to-private market in the UK in the late 1990s and onwards (see Figure 1), none looked at the motives of these transactions.

Figure 1: UK public-to-private activity



3 Theoretical and Empirical Foundation

First, we present the reader to the i) motives driving private equity firms to make a takeover bid. Second, we look at the ii) current takeover prediction models with a focus on their prediction power. We conclude with iii) existing gap we identify in the literature and how we contribute to close the gap.

3.1. Underlying takeover motives

In this section we explain the most prominent hypotheses of the motives for LBO transactions. We use them as a theoretical basis for the choice of variables to include in our takeover prediction model (see Section 4.3. Variable Selection). The hypotheses of the motives are divided into two groups: Value Creation Motives and Value Grasping Motives.

3.1.1. Value Creation Motives

One of the two sources of the high premiums in the public-to-private transactions can be post-transactional value creation. Cressy et al. (2007), for example, shows that after UK LBO takeovers operational profitability has increased by 4.5% in comparison to peer companies. Nikoskelainen and Wright (2007) confirm the results with a larger sample. Here we provide an overview of the most prominent value creation hypotheses:

- <u>The free cash flow hypothesis</u> builds on Jensen‘s (1986) work. He claims that managers with excess cash have incentives to build their empire by funding negative net present value projects rather than returning cash to the shareholders. This is especially likely for the large firms generating high cash flow and at the same time suffering from low growth prospects. Hence, reducing the liquidity and excess cash is important in eliminating agency costs and aligning management incentives with the owners. Theoretical explanation of the theory implies that the large companies are more prone to this problem in comparison to the small companies. Thus, the influence on the likelihood of a takeover might be different for large and small companies. This can explain the mixed empirical results in the models treating large and small companies as homogenous. Powell (1997) as well as Nadant and Perdreau (2011), for example, do not provide support for this hypothesis. On the other hand, Betzer (2006) does. We include proxies of this hypothesis into our model in order to check if separating small and large firms can explain the differences in the current empirical findings.

- According to the inefficient management hypothesis, if current management fails to maximize the firm value, takeovers become a mechanism for replacing them by more efficient managements (Marris, 1964). When management is not efficient to allocate the company's resources in the optimal way, the price of the shares decline below the price under optimal resource allocation. The inefficient management hypothesis is interlinked with the free cash flow hypothesis; however, the latter exclusively focuses on incentives and ignores the other reasons of inefficient resource allocation such as incompetence. For this reason, most of the authors include both of the hypotheses in their takeover prediction models. Powell (1997, 2001) does not find empirical support for this hypothesis in the UK takeovers. However, Barnes (1999, 2000) using different proxies for the same hypothesis finds that firms that underperform have higher likelihood of a takeover. Hyde (2009) showed that profitability is negatively correlated with the likelihood to receive a takeover bid. Given empirical support for the hypothesis, we choose to use this hypothesis when constructing our model.

- The control hypothesis finds its theoretical justification of takeovers in the free-rider problem on supervising management. When shareholders are dispersed, spending resources to actively monitor management does not pay off for a small stake owner (Grossman and Hart, 1980). As a result there is no active supervision of management. Public-to-private LBOs can create value by bringing an active owner with the strong incentives to invest in monitoring management and consequently reducing agency costs. Betzer (2006) shows that agency problem stemming from inactive owners does not influence takeovers while agency problem in relation to the free cash flow hypothesis does. Since control hypothesis is captured in either inefficiency hypothesis or the free cash flow hypothesis, inclusion of the proxies of this hypothesis would just result in model over-fitting, i.e. including more variables than needed. Moreover, empirics for the control hypothesis are poor. Thus, for these reasons we choose not to consider this hypothesis in our takeover prediction model.

- Although the firm size hypothesis got quite a lot of empirical support that size influences likelihood of a takeover (Powell 1997, 2004; Palepu, 1986; Ambrose and Megginson, 1992), authors do not seem to agree on how size influences the likelihood. On the one hand, Renneboog and Simons (2005) argue that for the small firms it becomes increasingly costly to be listed on the stock exchange; thus, the smaller the company, the more it is likely to be taken over. From this perspective, theoretical justification of the firm size hypothesis overlap with the transaction cost hypothesis. Powell (1997, 2004) gives another reason for the smaller companies to receive a takeover bid more often. He argues that acquirers struggle to absorb large companies. Although this argument is not entirely suitable for financial buyers since too large companies reduce fund diversification. When it comes to hostile takeovers, however, he finds that size is positively correlated with the likelihood of a takeover. Similarly, Nadant and Perdreau (2011) also find that targets are relatively larger companies. Due to the strong empirical support – although lack of agreement - for this hypothesis, we choose to include a size proxy in our model.

- Palepu (1986) introduces the growth-resource imbalance hypothesis to takeover prediction theoretical framework. The theory suggests that low-growth and resource rich companies as well as high-growth and resource-poor companies are likely to become LBO targets. This hypothesis is built on the premise that a buyer is either able to bring additional financing to support growth firms, or leverage a firm with rich resources but low growth prospects. Palepu's findings were also verified by Barnes (1990) and Powell (2004). This hypothesis is especially important in the context of financial takeovers since private equity firms are known for both bringing extra resources if needed and extracting extra cash. Some private equity companies specialize in 'buy-and-build' strategy, i.e. they buy companies with high growth potential and add on new acquisitions. Other private equity companies buy overcapitalized companies to eliminate this through high leverage. Due to the empirical support as well as high relevance to the financial LBOs, we choose to include the proxy for this hypothesis into our model.

3.1.2. Value Grasping Motives

Value grasping motives or wealth transfer hypotheses are the most controversial explanation of public-to-private transactions since it views private equity companies as winners at the others' expense. The most commonly discussed wealth transfer happens from stakeholders such as pre-transaction bondholders, employees, and the state in form of taxes to shareholders. The more recent studies also draw attention to wealth transfer between stakeholders within private equity firm, namely from Limited Partners of the fund (LPs) to General Partners (GPs). The LPs to GPs wealth transfer hypothesis, however, so far has not been applied and tested before in a takeover prediction model. Here we provide an overview of the main wealth transfer hypotheses:

- The wealth transfer from pre-transaction shareholders or the firm undervaluation hypothesis gives lower price than intrinsic value of the company as the main motive for the takeovers. This hypothesis is more prevalent in models predicting management buy-outs due to the asymmetric information (Harlow and Howe, 1993; Kaestner and Liu, 1996). However, it is also possible that outside knowledgeable investors spot that the intrinsic value of the company is larger than the current market capitalization (Renneboog and Simons, 2005). Betzer (2006) and Brar et al. (2009) show empirical support for the latter argumentation. Following them, we include proxies for this hypothesis in our model to check if relatively cheap companies have higher probability of being taken over.

- The wealth transfer from pre-transaction bond-holders hypothesis gives expropriation of pre-transaction bondholders as the reason for public-to-private transactions. Renneboog and Simons (2005) give three mechanisms to transfer value from pre-transaction bondholders to shareholders: increase in riskiness of investments, large increase in dividend payouts, or taking new debt of equal or higher seniority. Empirical support for the hypothesis is mixed. Marais et al. (1989) do not find losses for bondholders over their research period 1974-85. On the other hand, Travlos and Cornett (1993) empirical results show 1% statistically significant loss for bondholders. Cook et al. (1992) conclude that the losses to pre-transactional bondholders depend on the existence of covenants. According to Lehn and Poulsen (1989) the explicit covenants in the contracts dramatically increased in the end of the 80s. This means that explicit covenants in the contracts have become a common practice in our research period. Moreover, even without covenants, the transfer of 1% from pre-transactional bondholder would be too small to justify LBO. Thus, for these reasons we do not consider the pre-transaction bondholders wealth transfer hypothesis when we construct our model.

- Shleifer and Summers (1988) argue for the wealth transfer from employees hypothesis, i.e. the new shareholders reduce employment and compensation. Weston et al. (1998) do not observe hostility against employees in public-to private transactions. Mainly due to the absence of data on the change in compensation and employment after LBOs as well as lack of empirical support for the employees wealth transfer hypothesis, we do not consider the hypothesis when we construct our model.

- The wealth transfer in form of taxes hypothesis states that everything else held constant, a more leveraged firm has a higher value than a less leveraged firm (Modigliani and Miller, 1958). This makes the debt capacity of the firm an important investment consideration. The higher value of the leveraged firm is the result of the tax benefits. Additional loans create tax shields in the jurisdictions where interest costs are tax deductible. Nadant and Perdreau (2011) find empirical support for this hypothesis. Since our focus is LBO transactions, tax shields resulting from extra leverage might be an important motive. Thus, we choose to proxy this hypothesis in our model.

- The wealth transfer from LPs to GPs hypothesis builds on agency problem between investors in private equity fund and its managers. General Partners get "carried interest" equal to a percentage (usually 20%) of the profits above a certain hurdle rate (usually 8%). The carried interest coupled with the GP's contribution to the fund is thought to align GPs incentives with LPs (Kaplan and Strömberg, 2009). However, a limited liability and a call option-like carried interest on fund returns may increase the appetite for engaging in riskier deals since this would increase the value of the option. A General Partner who is in a position where he is "out of the money" for carried interest, might be incentivized to gamble on risky deals as he is approaching the end of the investment horizon (Axelsson et al., 2010).[4] Thorsell (Working Paper) brings this argument one step further and proves that GPs always have strong incentives to increase the risk of their investment. The LPs to GPs wealth transfer hypothesis so far has not been considered in the takeover prediction models as a potential motive for LBOs. We are the first to include the proxy for this hypothesis in our model.

3.2 Prediction Power of Existing Takeover Prediction Models

After the first LBO wave in the mid-70s in the US, many authors have tried to proxy previously mentioned hypotheses of motives and construct takeover prediction models. Especially studies using US data have been largely reflected in the academic literature due to the high takeover activity and thus large sample sizes. In comparison to North America, takeover prediction models are less researched in Europe, which partly can be explained by the smaller number of takeovers as well as delayed start of LBO activity in the European market. With the exception of several attempts to make a takeover prediction model in continental Europe (Betzer, 2006; Brar et al., 2009), the existing research mainly uses UK data, since most of the markets outside UK suffers from limited number of targets.

The early studies on takeover prediction modeling show very successful predictions with classification rates as high as 70-90%.[5] One of the earlier studies is made by Stevens (1973) in the US market during 1966-70. He achieves a correct classification prediction of 70% using a multi discriminant analysis on 40 targets and 40 non-targets. Stevens (1973) concludes that financial characteristics alone provide means to separate targets from non-

[4] Axelson et al., 2012 find empirical support that funds with lower expecting returns have an incentive to engage in riskier deals when studying international buyouts from 1980-2008.

[5] Classification rate is defined as correctly classified targets and non-targets in relation to total sample size.

targets. Belkaoui (1978) studies 25 takeovers in the Canadian market in the period 1960-68 testing the predictive value of different financial ratios using discriminant analysis. He achieves 85% classification rate. Dietrich and Sorensen (1984) manage to achieve even higher classification rate of 90% from studying 46 targets in the US 1969-73 using a binominal logit model.

The high prediction rates claimed by the authors of previous takeover prediction studies have been questioned and considered overstated by Palepu (1986) who has conducted a critical examination of the applied methodology. He points out three fundamental methodological flaws in the previous studies. First, applying non-random equal-share sampling overstates the probability estimates. Second, equal-share sampling distorts the sample proportion to the population and makes it non-generalizable. Third, using arbitrary cut-off probabilities makes the prediction accuracies difficult to interpret. Palepu (1986) then tests if the same prediction value could be achieved when adjusting for these flaws for listed manufacturing firms on NYSE from 1971-79. He uses the conditional maximum likelihood estimator proposed by Manski and McFadden (1981) in order to obtain unbiased estimates from a sample of 163 targets and 256 non-targets. His estimated model is statistically significant but has a classification rate as low as 46%.

Published studies following Palepu's (1986) paper has reported more moderate prediction levels. Espahbodi and Espahbodi (2003) achieved a classification rate of 62-63% when studying takeovers in the US 1993-97. Powell (1997) reports a classification rate of 47% when studying UK data 1984-91. However, Powell's (1997) main contribution is an empirical proof that characteristics of friendly and hostile takeovers differ and that the prediction power increases when this is taken into account. Thus, treating them as a homogenous group creates noise and leads to less significant results.

When evaluating the prediction power of takeover models, there are more factors to take into account than just classification rate. For example, a model with high classification rate does not necessarily mean it is capable of generating abnormal returns in a trading strategy. Barnes (1999) studied takeovers in the UK 1986-87 and reported very high classification rates of 91-98%. However, the high prediction accuracy could almost entirely be explained from correctly identifying only non-targets rather than targets. Unsurprisingly, Barnes (1999) model failed to earn abnormal returns. One measure that would be more appropriate from an investor's perspective is the proportion of correctly classified targets. This is further elaborated upon in section 4.7, when determining the optimal cut-off point of classification rule.

3.3 Contribution to existing literature

This paper attempts to close several gaps in the current literature. Firstly, the current takeover prediction model literature does not explicitly recognize that takeover rationales for small and large companies differ. For example, the transaction cost hypothesis is more likely to hold for smaller targets rather than for larger targets since the listing costs are proportionally larger for smaller companies (Kuhn Capital, 2003). Moreover, undervaluation due to small trading volumes is much more typical for smaller companies (Renneboog and Simons, 2005). Another reason applicable only to smaller targets is the lack of liquidity and expansion capital due to disregard by the institutional investors (Financial Times, Sept 17, 1999). Thus, we hypothesize that constructing prediction models that allow different characteristics for small and large targets will improve the prediction ability. Moreover, increased sample size due to the inclusion of failed takeover attempts could also potentially increase the prediction ability. Finally, the lack of existing research on LBO activity in the UK during 1998-2008 makes it interesting to check which hypothesis holds in the latest not researched takeover boom years.

Appendix 1 summarizes the support for different hypotheses from the previous studies.

4 Method

The method part consists of two parts i) Data and Sample Construction and ii) Model. In the first part, we explain choices we make to get our dataset. We describe targets, control group, sampling method, holdout sample, as well as rescaling of data. Method part follows to explain what statistical estimation technique we use, how we select variables to our model, how we test our model, as well as how we determine the optimal probability cut-off point.

4.1 Data and Sample Construction

4.1.1. Targets

The list of takeover attempts in the UK has been extracted from the Zephyr database. We have chosen to study the period from 1998 to 2008 capturing the buyout booms in 1999-2001 and 2006-2008. In order to control for takeover attempts occurring after our study period, we extract data from 1998 to 2009 from Zephyr database. A target is defined as a company being publicly traded at the time when the takeover offer is received of minimum 50% acquired ownership stake. Since we study manufacturing companies, service sectors are excluded in our target sample.[6] Further, as our purpose is to study financial buyouts, we include only financial acquirers.[7] After filtering in accordance with the above conditions we end up with 104 targets.

The list of acquirers was cross-checked to see whether the financial buyout criterion were fulfilled. This consequently leads to a drop of targets from 104 to 94 targets in our target sample size of which 46 are considered ”Large” and 48 are ”Small”. To define “Large” and “Small” firms we have chosen GBP 80 million in market cap as our size limit using the OMX Nordic Small Cap size limit of EUR 100 million as guideline.

Figure 2 shows the distribution of the takeovers over our study period. The graph illustrates the buyout wave in the UK during our study period. Further, it is evident that the LBO industry is highly cyclical and affected by crises.

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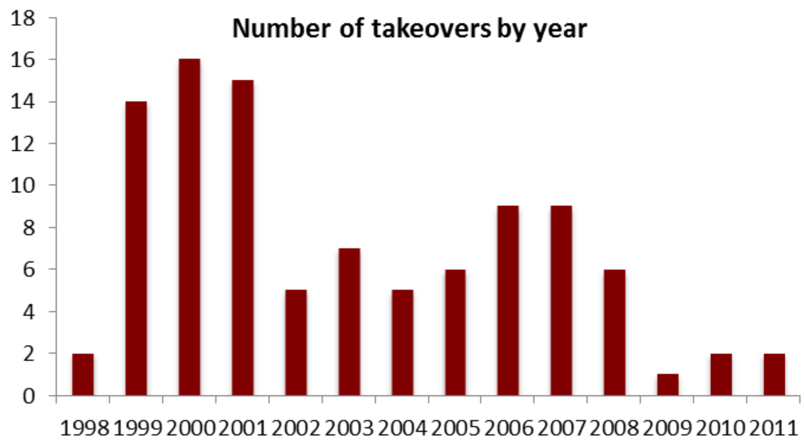
[6] Sectors in Zephyr defined as Banks, Insurance, Education & Health, Hotels & Restaurants, Other services
[7] Defined as “leveraged buyout” and “private equity” in type of deal financing in Zephyr

Figure 2: Distribution of takeovers over 1998-2008

Year	Takeovers
1998	2
1999	14
2000	16
2001	15
2002	5
2003	7
2004	5
2005	6
2006	9
2007	9
2008	6
Total	94



Due to missing data, two targets were dropped making our final target sample to consist of 92 companies.

In Datastream, a company has a ticker code for each time it gets listed on the stock exchange, which means that a company could have several ticker codes if it has been subject to multiple takeovers. Thus, we control that the ticker code in Datastream corresponds to the correct takeover year for the targets obtained from Zephyr.

Choosing the length of the lag between the date when the explanatory variables are measured and the date when the bid is announced is a trade-off. On the one hand, we want to have long enough lag to minimize the risk of information leakage that increases the price of the shares before the actual announcement. This is important because our prediction model will be potentially applied for trading strategy; thus, our model should enable an investor to earn abnormal returns by buying shares of a likely target cheaply, i.e. before the information of the likely takeover has boosted share prices. On the other hand, we want to have short enough lag to make sure that the measured accounting ratios incorporate as much information about upcoming takeover as possible (Hyde, 2009).

Authors of the prior takeover prediction models balance these two competing goals differently. Powell (1997), Barnes (2000), and Lee (2010), for example, measures explanatory variables at the accounting year-end prior to the observation year. Thus, the lag in their research can be as long as one year. This also creates cross-sectional variation of up to one year. Contrarily, Betzer (2006) and Hyde (2009) have much shorter lags. They measure the explanatory variables prior to the LBO announcement date two months and three months respectively.

We choose to extract variables two accounting quarters prior to the announcement date. Since only quarterly data is available and takeover announcements can be in the beginning of the quarter or in the end of the quarter, it practically means that we measure the explanatory variables three to six months before the announcement day. According to Jensen and Ruback (1983), prolonging the lag more than three months would result in difficulties to predict LBOs from accounting ratios. At the same time, given that we have quarterly data, extracting variables one accounting quarter prior to the announcement would mean that in case the announcement is made in the beginning of the quarter, the accounting ratios would be measured just before the announcement. This would make our model less applicable in the investment strategies since the window of opportunity for the investors would be too short. Thus, we think that measuring two accounting quarters prior to the announcement date best balances the trade-off between having information in the accounting ratios but no leaked information into the market.

4.1.2. Control Group

The sample of non-targets was constructed by including all firms in the London stock exchange from 1998-2011, excluding the financial and service related industries in accordance with the selection of targets in the previous phase. Further, a minimum market cap of GBP 10 million is required in order to be included in the sample ensuring a minimum level of liquidity. After omitting for missing data in Datastream and controlling for that no takeovers occurred during our study period extended by three years[8], our non-target sample size amounted to 870 firms.

[8] In order to control for any lag effects of our prediction model

4.1.3. Sampling Method

The two main sampling methods are either randomly based or stratified sampling. In a random sampling, firms get selected to the estimation sample on a purely random basis; hence, the proportion of the targets in the population is reflected in the estimation sample. In a stratified sampling the population gets divided into sub-groups based on some variables of which the samples are selected from.

As proven by Manski and Lerman (1977), a pure random sampling in our case could lead to a non-explanatory model since the number of targets is too few in relation to non-targets. On the other hand, a stratified sampling does not reflect the true ratio between targets and non-targets in the whole population and, as a result, may lead to a bias in our modeling (Cosslett, 1981). Thus, on one extreme random sampling may result in non-explanatory model and on the other extreme stratified sampling with 1:1 target and non-target ratio would lead to bias in our modeling.

In order to avoid non-explanatory model we use stratified sampling. Similarly, in order to minimize bias in our model, we follow Palepu's (1986) recommendations. He states that the magnitude of the bias is directly proportional to the difference in the sampling ratios of the targets and non-targets. Thus, increasing the ratio between targets and non-targets in our sample should reduce the prediction bias of our model compared to an equal-share based sampling since it is a closer approximation of the true proportion of targets in the whole population. Moreover, we eliminate the remaining bias by adjusting our estimated probabilities with Bayes' formula.[9]

We separate the pools of targets and non-targets into large and small firms. Then we assign two non-targets to each target according to the takeover year on a random basis, meaning we have a 1:2 ratio between targets and non-targets in our sample. We choose 1:2 ratio since authors in the previous takeover prediction literature used ratios around 1:2. Palepu (1986), for example, uses 1:1.6 ratio while Hyde (2009) uses 1:2.5 ratio.

[9] Powell, 1997 claims that the bias in the logit model introduced by choice-based sampling only affects the constant term (Cosslett, 1981; Maddala, 1983). However, in his later article in 2004 he uses pooled sampling and criticized choice-based sampling.

When matching the control group with the targets we have to account for survivorship bias since the list of non-targets for a certain time period only includes firms that have been listed throughout the whole period. Hence, firms that got listed or delisted during the period would be neglected during the random selection process to the estimation sample. In order to cope with the survivorship bias, we divide the population into yearly subgroups since data needs to be gathered corresponding to the takeover year[10] of the target. We then reconstruct each year by including both active and dead firms obtained from Datastream in the sub-groups, which makes "dead" firms selectable to the estimation sample in the years they were still listed. Consequently, a non-target that has been listed during the whole period will also have a higher probability of being selected to the control group, since the number of "chances" of being selected for each year is higher than a firm that has not been listed throughout the whole period.

4.1.4. Holdout sample

In order to test the prediction accuracy outside the estimation sample, authors of the earlier studies have used different approaches. Some authors have left part of the sample as a holdout sample. For example, Palepu (1986) has left one sixth of the total estimation sample as a holdout sample. Other authors (Powell, 1997; Barnes, 1999; Hyde, 2009) have used consequent years of the study period for testing the prediction model. We cannot apply the latter way of testing the prediction accuracy of our models outside the estimation sample since in 2009-2012 there are only five targets fulfilling our definition. Thus, instead of using consequent years, we leave part of our sample for holdout testing.

Proportion of the estimation sample left as a holdout sample has to reconcile two conflicting goals. On the one hand, the holdout sample should be large enough to reflect the same distribution of firm characteristics as in the population. On the other hand, losing out on too many data points in the estimation sample could decrease the robustness of our inferences from logistic regression models. Bergtold et al (2011), for example, showed that in logistic regression models mean estimated bias significantly reduces when the sample size reaches 250.

[10] Takeover year is defined as the rolling year in the period of two quarters precedent the announcement date

Our sample size has already become limited after separating for large and small firms. Thus, balancing a trade-off between having robust inferences from the models (requires large estimation sample) and having robust inferences about the accuracy of our model (requires large holdout sample) in the holdout sample becomes difficult. To start with, the robustness of a model is imperative for the model to be accurate. Thus, to insure robust results, we keep estimation sample close to Bergtold's et al (2011) recommendation of 250. Large enough estimation sample comes at the expense of holdout sample. We leave out a small portion of one eighth as the holdout sample. Hence, our total estimation sample consists of 248 (81 targets and 167 non-targets) leaving 33 firms (11 targets and 22 non-targets) in the holdout sample.

We acknowledge though that a sample of 33 is too small to make robust inferences of the prediction accuracy of our model; however, leaving a larger proportion for holdout sample is too costly for us. Thus, we use prediction accuracy numbers from holdout sample just to verify results about the classification accuracy in the estimation sample rather than to get specific numbers.

4.1.5. Rescaling of data

A good prediction model needs to be stable over time and across industries. Accounting ratios tend to vary over time (changes in price levels, accounting policies, business cycle; Platt et al. [1994]) and across industries. For this reasons, Barnes (1999) uses industry-relative data where a firm's raw accounting ratio is divided by the industry average for each corresponding year. Essentially, this measures a firm's individual rank within the distribution of the industry relative to its mean, hence adjusting for industry differences. The implication of using industry-relative data is that firms with financial characteristics deviating from industry norms face higher likelihood of takeover which ensures that the results are more cross-sectionally stable over time.

Powell (1997) shows that the prediction power increases when industry-relative data is used. However, it is difficult to conclude whether the improvement could be attributed to mitigation of industry differences or the time inconsistency problem. However, Barnes

(1999) points out a flaw that general models based on industry-relative data will lead to higher error rates. Applying the same denominator ratio enforces similarities for all firms even though they in fact are dissimilar. This is especially related to firms from industries that are not well represented in the estimation sample.

In order to mitigate the aforementioned time inconsistency problem, we choose to, in parallel with our original data, also regress data rescaled by the average of the estimation sample for each year. We do this to compare and verify that the conclusions we draw from our original regression results do not changes.

4.2 The Model

4.2.1. Statistical Estimation Technique

The alternative statistical estimation techniques used in the previous takeover prediction literature are logistic, probit or multiple discriminant analysis (MDA). We use the binomial logistic model to calculate the probabilities for a firm to get a takeover offer. Our choice is mainly based on statistical properties of our data.

We choose logit model over MDA because MDA's assumption that explanatory variables are jointly normal and has the equal covariance matrices is too restrictive for our dataset of the financial explanatory variables. Financial ratios are not jointly normal, are skewed and have fat tails. As shown by Press and Wilson (1978), application of MDA when this assumption is violated results in meaningless explanatory variables included in the model. Logistic model, on the other hand, correctly shows zero coefficients. Moreover, in a comparative study of the two estimation techniques Jones (1987) proved that logit model is slightly more accurate. Thus, based on the better fit of our data to the logit model assumptions and recommendations of the previous literature, we choose logistic regression.

The choice between Logistic and Probit model is not that straightforward. One reason for choosing logistic regression is easier interpretation. Probit coefficients indicate how much one unit increase in explanatory variable increases z-score while logistic regression models log odds. We assume that for this reason, the choice of Probit model is rare in the existing literature of takeover prediction models. Although logit and probit functions' curves differ, namely probit moves to the axis faster resulting in fatter tails, the difference is slight. Thus, based on the easier interpretation of the coefficients as well as more extensive empirical proof that logistic model is appropriate to compute takeover prediction model, we stick to logistic regression.

Binary logistic model has the following assumptions. First, the model should be fitted correctly. Missing meaningful variables would result in model under-fitting and including meaningless variables would result in model over-fitting. To insure a good fit we use stepwise method to estimate the regression. Afterwards, we assess *goodness-of-fit* (Hosmer & Lemeshow, 2000). Error terms have to be independent. To check if error terms are independent we look at their statistics such as mean, skewness, and kurtosis. We also use Wilcoxon signed-rank test. The model should have no or little multicollinearity. To make sure that variables are independent from each other we exclude one of the two variables if correlation between the variables is higher than 50%. In addition, to check severity of multicollinearity in the predictors we also use variance inflation factor. Finally, sample size should be large enough. Bergtold et al (2011), for example, showed that in logistic regression models mean estimated bias significantly reduces when the sample size reaches 250 and increases if the sample is smaller than 100.

Equation (1) gives logistic probability function of the measured characteristics of the firm.

$$P(Y_i = 1 \mid X_i) = \frac{1}{1+e^{-X'\beta}} \tag{1}$$

Y_i is a binary outcome variable equal to 1 if the firm i received a takeover offer and 0 otherwise. The probability of a firm i to receive a takeover offer is determined by the measured firm's characteristics that enter the model as well as estimated coefficients. The precise specification of $X'\beta$ is given in Equation (2). The next section discusses the choice to include these specific variables.

$$X'\beta = \beta_0 + \beta_1 ROA + \beta_2 ATO + \beta_3 OPM + \beta_4 \frac{Cash}{Sales} + \beta_5 \frac{FCF}{Sales} + \beta_6 logA + \beta_7 GRI + \beta_8 \frac{EV}{EBIT} + \beta_9 \frac{N}{E} + \beta_{10} \frac{Tang}{TA} + \beta_{11} logSDROIC \quad (2)$$

4.2.2. Variable Selection

Different approaches have been used in earlier studies when choosing the variables to include in the prediction model. Simkowitz and Monroe (1979) start with a broad set of ratios. They plug 24 ratios and then drop the least statistically significant variables in a step-wise procedure until all the variables show statistical significance. However, this approach is criticized by Palepu (1986) for model over-fitting. Benishay (1971) raises the issue that using several proxies for a particular variable could lead to multicollinearity and bias in the prediction model. More recent studies (Powell, 1997, 2004; Hyde, 2009) include variables on the basis of pre-determined hypotheses. In line with Palepu's (1986) recommendation as well as practice of more recent studies, we choose variables according to the hypotheses of the motives of public-to-private transactions described in Section 2.

Next is a more detailed discussion of the rationalization of our selection of explanatory variables to proxy hypotheses and the composition of the variables used in our initial regression model. A detailed definition and computation of the variables can be seen in Appendix 2.

Inefficient management

Previous authors in this field of study have divergent views how to proxy the inefficient management hypothesis. Palepu (1986) argues that excess stock return calculated using market model and daily stock return data is a better proxy than accounting profitability measures since the latter measures only current performance. On the other hand, Powell

(1997, 2001, 2004) prefers accounting ratios since they are less volatile. Due to the same reason, we include accounting ratios to proxy the inefficient management hypothesis. Palepu (1986) uses return on equity. However, we include *return on assets* (ROA) as a proxy for two reasons. First, we want to analyze operational efficiency on all internal resources unconditional of the financing. Further, we expect the ROA to be less volatile and more stable over time. To get insights into what type of inefficiencies affect likelihood of takeover bid, we complement ROA with asset turnover ratio (*Sales to Assets*), profit margin *(EBIT to Sales)*.

For the large firms, we hypothesize that a decrease in the ratios that proxy the inefficient management hypothesis increases the likelihood of receiving a takeover bid since that would indicate room for improvement and value creation opportunities (given that the potential for improvements is not priced). For the small firms, we hypothesize that the variables can take both signs since firms that are efficient but lack growth resources could also be potential targets for takeover offers.

Explanatory variables:	*Expected sign for large*	*Expected sign for small*
Return on Assets	*(-)*	*(-/+)*
EBIT to Sales	*(-)*	*(-/+)*
Sales to Assets	*(-)*	*(-/+)*

Undervaluation

According to Palepu (1986), Tobin's q should be included to see if the firm is undervalued. However, due to absent or inconsistency in calculating replacement costs, Palepu (1986) as well as more recent researchers such as Powell (1997, 2001, 2004) and Maupin (1984) include market-to-book ratio. On the contrary to this practice, we have chosen to use the enterprise value to EBIT ratio (EV to EBIT) as proxy for undervaluation.[11] We aim to tailor the proxy to our specific topic, i.e. leverage buyouts where private equity investors are

[11] Interestingly enough, when replacing EV/EBIT with M/B in our model, the latter shows to be insignificant whereas the former is highly significant

looking at the total value of the firm unconditional of the financing (enterprise value) rather than the equity part since they will have to take over the existing debt or refinance it. This is also the explanation why we have chosen EV to EBIT rather than the other valuation multiples such as price to earnings (P to E) used for example by Betzer (2006). Further, we choose to measure EV in relation to EBIT rather than EBITDA since we believe this is a closer approximation of the cash flow generated by the firm. Our estimation sample consists of manufacturing companies who arguably is more capital intensive and in need of capex which makes depreciation an important cost to take into account.

Unambiguously, for both large and small firms, we hypothesize the EV to EBIT to have a negative sign which indicates undervaluation and potential for higher returns for the investor.

Explanatory variables:	*Expected sign for large*	*Expected sign for small*
Enterprise value to EBIT	*(-)*	*(-)*

Free Cash Flow Hypothesis

As explained earlier in Section 2, excess cash may indicate mismanagement of the firm's resources which would increase the likelihood of being a target. As a proxy for this hypothesis, Powell (1997, 2001, 2004) uses operating cash flow to total assets. Loh (1992) has done the most extensive analysis how to proxy free cash flow. He uses three financial ratios – cash flow to market value of equity, cash flow to sales, and cash flow to interest. However, only cash flow to sales is statistically significant. Based on the findings of Loh (1992) and Betzer (2006), we choose to include free cash flow to sales (*FCF to Sales*) as well as cash to sales as proxies for the free cash flow hypothesis. Further, putting cash flow in relation to an income statement measure also gives an indication of the cash conversion ability of the company.

For the large firms we expect the ratios that proxy the *FCF hypothesis* to have a positive sign. For the small firms, we hypothesize that the sign could also be the opposite since they are more likely to be in a growth stage and lacking the cash flow and liquidity for expansion.

Explanatory variables:	*Expected sign for large*	*Expected sign for small*
Free cash flow to Sales	*(+)*	*(+/-)*
Cash to Sales	*(+)*	*(+/-)*

Firm Size

Log of total assets has been the dominant proxy for size in the previous studies and also turned out to have significant prediction power (Stevens, 1973; Dietrich & Sorensen, 1984; Palepu, 1986). Barnes (2000) instead uses market capitalization while Brar et al. (2009) employ three measures – market capitalization, sales, and number of employees. For our model we use log of assets which is more stable and also the most commonly used.

We expect the variable to have a negative sign in line with the findings from previous studies. Renneboog and Simons (2005) argue that for smaller firms it becomes increasingly costly to be listed on stock exchange in a relative perspective. Powell (1997, 2004) argues that when it comes to takeovers, acquirers struggle to absorb large companies.

Explanatory variables:	*Expected sign for large*	*Expected sign for small*
Log of total assets	*(-)*	*(-)*

Growth-Resource Imbalance

Palepu (1986) has introduced the growth-resource imbalance dummy in takeover prediction modeling. He includes a dummy variable that is equal to one if a firm has high (low) growth combined with low (high) liquidity and high (low) financial leverage. He proxies growth as average change in sales, liquidity as liquid assets to total assets and leverage as debt to equity ratio. Similarly, Powell (1997, 2001, 2004) includes a dummy to proxy growth-resource imbalance. Barnes (2000) adds additional ratios to the ones used by Palepu (1986), namely the sum of profits and interest divided by interest, current ratio, asset turnover as well as total remuneration to asset ratio. Following Palepu's (1986) approach, we use two-year sales growth, cash to sales and debt to equity ratio. To classify whether each of the variable is high or low, we use the median of the estimation sample as a cutoff.

We do not expect the signs to differ between large and small since the growth-resource dummy takes the value of 1 for both states of the growth-resource combination.

Explanatory variables:	*Expected sign for large*	*Expected sign for small*
Growth-resource dummy	*(+)*	*(+)*

Wealth transfer in the form of taxes

The hypotheses we would like to proxy related to wealth transferring are tax benefits due to increased financial leverage and the GP[12] versus LP[13] conflict. As shown empirically by Ambrose (1990) and Ambrose and Megginson (1992), high tangible fixed assets as a proportion of total assets increase the likelihood to become a target for takeover. Powell (1997, 2001, and 2004) also uses this ratio as a proxy for real property hypothesis. This ratio indicates capacity for financial leverage in LBO and has been included in our model. We also choose to include a more direct measure of leverage, net debt to equity ratio, widely used in the earlier studies (Palepu, 1986; Powell, 1997; Barnes, 1999).

[12] General Partners are active in the private equity firm's day-to-day operations and are the decision-makers of the investments made by the fund

[13] Limited Partners to a private equity firm are the investors and fund providers and do not have any management responsibility nor decision rights in the investments (hence the limited partnership)

Recent studies relating to the GP-LP agency conflict have usually used several financial leverage ratios such as log of total debt divided by EBITDA and debt divided by enterprise value (Axelson et al., 2012) to study the incentive to engage in riskier deals. In order to cover the total risk of an investment we have chosen to also include a second component of operational risk since this should hold under the same reasoning as with increasing the risk by financial leverage. Hence, the log of standard deviation of the return on invested capital[14] (*log SD-ROIC*) has been included in our model.

The net debt to equity is expected to have a negative sign since low leverage is an indicator of excess capacity for taking on additional debt, making a buyout more attractive. Similarly, high ratio of tangible to total assets signals higher debt capacity which makes us to hypothesize a positive sign. When it comes to log of ROIC volatility it is not as clear-cut. From a debt capacity perspective, low volatility should indicate more room for financial leverage. But on the other hand, the conflict of interest between GPs and LPs would indicate that GPs are more prone to invest in volatile firms which would make us expect a positive sign. Hence, we can conclude that the variable of log SD-ROIC can take both signs. We do not hypothesize that the signs for small firms should differ from large.

Explanatory variables:	*Expected sign for large*	*Expected sign for small*
Net debt to Equity	*(-)*	*(-)*
Tangible to Total Assets	*(+)*	*(+)*
Log of SD(ROIC)	*(+/-)*	*(+/-)*

4.2.3. Model Construction

As outlined in the previous section, we use accounting ratios as proxies of the hypotheses of takeover motives in order to predict targets. Some of these accounting ratios could be similarly computed and thus there is a risk of multicollinearity between some of the variables (Barnes, 1999). Prior to constructing our model we first check for correlation

[14] Return on invested capital does not differ materially from return on capital employed but has been used due to direct availability in Datastream

between each variable. If the correlations exceed 50%, one of the variables is dropped. None of the variables that were intended to be run in our initial regression were dropped. Later we also test the whole model itself for multicollinearity. We start constructing our models with the following initial regression that includes all before mentioned proxies:

Figure 3: Accounting Ratios to Proxy Hypotheses of Takeover Motives

Explanatory variable	**Main hypothesis**	**Specific hypothesis**	**Expected sign**	
			Large	*Small*
Return on Assets	*Wealth creation*	Inefficient mgmt	-	-/+
Sales to Assets	*Wealth creation*	Inefficient mgmt	-	-/+
EBIT to Sales	*Wealth creation*	Inefficient mgmt	-	-/+
FCF to Sales	*Wealth creation*	FCF	+	+/-
Cash to Sales	*Wealth creation*	FCF, Growth-resource	+	+/-
Log of Assets	*Wealth creation*	Firm size	-	-/+
Growth-resource dummy	*Wealth creation*	Growth-resource	+	+
EV to EBIT	*Wealth transfer*	Undervaluation	-	-
Net debt to Equity	*Wealth transfer*	Tax benefit	-	-
Tangible to Total Assets	*Wealth transfer*	Tax benefit	+	+
Log of SD ROIC	*Wealth transfer*	Tax benefit, GP-LP conflict	+ / -	+ / -

We run the regression i) with the sample including all companies ii) with the sample of small companies iii) with the sample of large companies. We use the initial regression to test which of the motives can and cannot explain LBOs for the three samples. In the final models for the three samples we include only the proxies of those motives that can explain LBOs. Thus, the initial regression is just a starting point to get takeover prediction models for i) both small and large companies ii) small companies iii) large companies.

To get the final model we start with the initial regression that includes all the proxies of the hypotheses of motives and delete the most insignificant variable one-by-one until all the variables in a model are statistically significant. This backward stepwise procedure is done separately for each three samples to obtain the final takeover prediction model for all companies as well as separate models for the large and for the small companies. Alternatively to backward stepwise procedure, we could choose either forward stepwise procedure or a mix of backward and forward procedures. In the forward procedure, the starting point is empty model without any variables and then the most significant variables are added one-by-one until all the variables that meet set criteria are added. In the mix of backward and forward procedures, variables that meet entry criterion set by the user are added and variables that meet removal criterion are removed until there are no variables to add or remove (Flom and Cassell, 2007). We have chosen to use backward stepwise procedure as opposed to forward stepwise procedure or a mix of two since most of the previous authors of takeover prediction models (e.g. Lee, 2010) or bankruptcy prediction models (e.g. Skogsvik, 1988) use backward stepwise procedure.

In order to get a good model with stepwise regression, we have to balance a trade-off between over-fitting the data and missing variables that explain takeover activities. On the one hand, starting with the large number of the accounting ratios as explanatory variables and then trying to find 'the best' model may lead to over-fitting the data (Flom and Cassell, 2007). Palepu (1986) criticized earlier takeover prediction models for starting with many popular accounting ratios and then leaving statistical significance to define the final model[15]. On the other hand, we want to try as many potential explanatory variables as possible to be sure that we do not miss important explanatory variables.

We balance the trade-off between over-fitting the data and missing important explanatory variables in two ways. First, as discussed in Variable Selection section, we selectively choose which variables to test in the initial regression based on the motives of LBOs. Thus, instead of just plugging all accounting ratios to test in the initial model, we limit the possibility to over-fit the data by selectively choosing variables that are backed with theory of takeover motives. At the same time, our initial regression includes variables that proxy all main hypothesis of takeover motives. This limits the possibility to miss important explanatory variables in the final models. Secondly, we set significance value lower than 10% as the criterion to remove the explanatory variable from the final models. According to (Newbold et al., 2012) 10% significance level is already quite low. Low removal criterion limits to over-fit the data. On the other hand, in order not to miss any significant

[15] Simkowitz and Monroe (1971), for example, plugged in 24 accounting ratios in their initial regression. After stepwise procedure their final model included 7 ratios.

explanatory variables, we also check how the model changes when we loosen the criterion to 15% significance level.

As mentioned, in the final models we include only statistically significant proxies of the motives. Freedman (1983) has showed that inclusion of totally unrelated explanatory variables in the final model boosts explanatory power of the model. Thus, leaving insignificant variables in the final model would result in artificially high pseudo-R^2. To avoid this, we exclude insignificant variable in the stepwise procedure. Naturally pseudo-R^2 in the final models will go down just because they will have fewer explanatory variables than the initial regression. Overall, this means that pseudo-R^2 of the initial regression with many insignificant explanatory variables that artificially boost explanatory power is not comparable with pseudo-R^2 of the final models that are 'clean' from the insignificant variables.

4.2.4 Model Testing

Finally, after model building stage when we have the final models with only significant variables, we use statistical tests to assess the model and check for influential observations.

To start with, we check if our data does not violate assumptions of logistic model. We use *Wilcoxon signed-rank test* to check if residuals are independent. This test compares the medians of the residuals in the two groups: residuals of predicted variables equal to 0 (non-targets) and residuals of predicted variables equal to 1 (targets). If the medians in the two groups differ significantly, residuals are influenced by the outcome variable and the independence of residuals assumption is violated. Low p-value of Wilcoxon signed-rank test shows that the residuals are influenced by the outcome variable; thus, dependent. High p-value for shows that hypothesis that the difference of the median is equal to 0 cannot be rejected; thus, the residuals are independent.

The second assumption that should hold is no or little multicollinearity. In the initial model we have checked correlation between variables and excluded one of the two if the correlation is higher than 50%. However, looking at the pair correlation only is limiting since linear correlation can appear when the third or fourth variables are introduced. Thus, we use *Variance Inflation Factor (VIF)* to check for multicollinearity in the whole model. If multicollinearity exists, explanatory variables are linearly correlated with each other. This prohibits estimation of unique coefficients. As a result, coefficients become unstable or, in other words, have high standard errors. Thus, to detect multicollinearity we use Variance Inflation Factor (VIF). We reject multicollinearity problem in the model if VIF values are smaller than 10 (Myers 1990).

To see if our LBO prediction models are good overall, we look at the likelihood *ratio chi-square test* statistic to compare these models with the 'empty' model, i.e. a model without independent variables or iteration 0. We check the probability to get the same chi-square statistic without any effect of explanatory variables on the outcome variable. If we get small p-values, we reject null hypothesis that our model and 'empty' are the same; thus, our model is better than the empty model.

To check if our model is effective in describing dependent variable, we use *goodness-of-fit* tests. These tests look at the distance between observed outcome value and predicted outcome value. If the distance is small and unsystematic, the model passes the goodness-of-fit test. First, we use *Pearson Chi-Square test*. If the test is not statistically, our models fit reasonably well the data. In order to test if our models equally well fit to all groups of data, we use *Hosmer-Lemeshow test* that uses grouping according to the values of estimated probability. Similarly, if p-value is high, hypothesis that the model is fitted to all groups of the data cannot be rejected.

Finally, in order to detect influential observations, we use three techniques: hat diagonal (*leverage*), deletion displacement (*delta beta*), and deletion chi-square (*delta chi-square*)[16].

[16]The hat diagonal technique shows leverage of the observation on the regression curve. Deletion displacement technique shows how regression coefficients change when all observations with the same covariate pattern are deleted. Deletion chi-square shows how the fit of the regression changes when all observations with the same covariate pattern are deleted (Hosmer & Lemeshow, 2000, p. 167-186).

If two out of these three techniques indicate that the same single observation has a significant impact on the model, we drop the observation to make sure that the results of the model are not distorted by the observation (Hosmer & Lemeshow, 2000).

4.2.5. Probability Cut-off Point

Since our objective is to construct a model that predicts potential takeover targets, we would need to test the predictive accuracy of our model and the classification of target and non-targets. We do this by applying a classification rule where the estimated probabilities are compared to a cut-off probability. A firm will be classified as a takeover target when the estimated probability is higher than the cut-off and a non-target if it is lower.

The determination of an "optimal" cut-off probability depends on the decision context in where the model is used. The purpose of our prediction model is to use it as a stock market trading strategy. Prior studies have just chosen arbitrary cut-off points (Dietrich & Sorensen, 1984, used 50%) which has been criticized by Palepu (1986) for making the results different to interpret. Palepu (1986) has tried to rectify this problem by optimizing the cut-off probability so that the expected pay-off from an investment portfolio would be maximized. His optimal classification scheme implied that the expected costs of Type I (classifying target as non-target) and Type II (classifying non-targets as targets) errors are equal. However, if the objective is to maximize abnormal returns this assumption would be erroneous. Investing in non-target firms would be more costly for the investor than misclassifying a target as a non-target since the former would lead to dilution of abnormal returns. This flaw has been stressed by Powell (2004) who has argued that the costs are neither equal nor constant. Instead the optimal portfolio selection criterion should be to maximize the proportion of target firms rather than minimizing the absolute number of misclassifications. Powell (2004) has operationalized this by calculating the takeover probabilities for all firms in the estimation sample and dividing the probabilities into deciles. The decile with the highest proportion of targets will then be used as cut-off point. We have chosen to apply the same procedure for determining our cut-off probability. In the sample of large firms we get an optimal cut-off point of 0.3554, and for small firms we get 0.6365.

The cutoff points for each decile in the estimation sample of large and small firms can be seen in Appendix 3.

5 Empirical Results and Discussion

In this section, we present our results, analysis and implications. First, we compare all three models: i) do they differ for small and large LBOs ii) what implied motives drive the small and large LBOs. Then, we look iii) if made-to-size models improve prediction accuracy. We conclude with implications of our analysis.

5.1 Comparison of the Models

In below tables, we present all three final models including only the explanatory variables at 5% significance level.

Figure 4: Generic Model

MODEL FOR SMALL AND LARGE	
Number of obs	225
Likelihood Ratio	32.18
p-value	0.00
Pseudo R^2	0.11

	Coef.	Std. Err.	P>|z|	Odds Ratio
ROA	2.10	0.95	0.03	8.19
EVtoEBIT	-0.05	0.02	0.01	0.95
CashtoSales	-6.19	1.97	0.00	0.00
LogofAssets	0.40	0.19	0.03	1.49
LogSDROIC	0.29	0.14	0.04	1.33
Constant	-2.32	1.08	0.03	0.10

Figure 5: Made-to-Size Models

MODEL FOR SMALL	
Number of obs	127
Likelihood Ratio	35.04
p-value	0.00
Pseudo R^2	0.22

	Coef.	Std. Err.	P>|z|	Odds Ratio
ROA	2.92	1.31	0.03	18.53
EVtoEBIT	-0.06	0.03	0.03	0.94
LogofAssets	2.02	0.56	0.00	7.52
SalestoAssets	0.54	0.18	0.00	1.71
Constant	-10.00	2.69	0.00	0.00

MODEL FOR LARGE	
Number of obs	107
Likelihood Ratio	21.03
p-value	0.00
Pseudo R^2	0.15

	Coef.	Std. Err.	P>|z|	Odds Ratio
EBITtoSales	4.10	1.96	0.04	60.29
ROA	-6.23	2.56	0.02	0.00
CashtoSales	-9.79	3.46	0.01	0.00
LogSDROIC	0.87	0.29	0.00	2.40
Constant	-1.60	0.71	0.03	0.20

Overall, we can see that variables from both the made-to-size models are nested in the generic model (ROA, EV to EBIT, Cash to Sales, Log of Assets, Log of Standard Deviation of ROIC). However, in comparison to each other, the two made-to-size models are completely different. When we partition the sample into small and large companies, all predictors in the model for the small LBOs are different than in the model for the large LBOs. ROA is a significant explanatory variable in both, but with the opposite signs (positive for small, negative for large). Further, high EBIT to Sales, ROIC volatility and low cash to sales increase the likelihood for large firms to become takeover targets. For small firms, the significant variables are low EV to EBIT, high assets and asset turnover. Overall, we conclude that the firm characteristics of small and large LBOs differ significantly.

Conclusion 1: Firm characteristics of small and large LBO targets differ significantly.

Since characteristics of the small and large targets differ, prediction model that is supposed to be able to predict both small and large targets is prone to flaws because it does not allow predictors to reflect the differences in characteristics. For example, if we used generic model to predict whether a large company is likely to be taken over, we concluded that a high ROA ratio increases the likelihood. The made-to-size model, however, shows that high ROA ratio for the large companies in fact decreases the likelihood to receive a takeover bid. Positive sign of ROA ratio in the generic model is clearly driven by the sample of small companies that outweigh the influence of the smaller sample of the large companies. Thus, different characteristics of the small and large targets mean that good prediction modeling requires constructing different models for small and large firms.

Conclusion 2: Not acknowledging the differences between small and large LBOs could lead to misleading takeover prediction results.

We see in the tables that partitioning the sample into two samples according to the size of the firm and tailoring the model for each sample separately increases the explanatory power. Pseudo R^2 increases from 0.11 to 0.22 in the model for small LBOs and to 0.15 in the model for large LBOs. Pseudo R^2 increases even given that the number of explanatory variables has decreased.

Conclusion 3: Separating small from large firms in prediction models increases the explanatory power.

5.2 Motives that Drive Small and Large LBOs

In this section, we look at the predictors of the small and large LBOs in relation to the hypotheses of the motives that these explanatory variables proxy. Since the empirical results show that characteristics of the small and large targets differ, motives that drive small LBOs and large LBOs are likely to differ too. Below, we discuss which motives drive small LBOs and which motives drive large LBOs. We also relate our findings to what previous authors have found.

Small LBOs

When it comes to the small LBOs, empirical findings support only the *undervaluation hypothesis*. Overall, we find that the likelihood of receiving a takeover bid increases when EV-to-EBIT decreases and when ROA, Asset Turnover, as well as Assets increase:

- EV-to-EBIT ratio proxy the *undervaluation hypothesis*. As expected, sign of the ratio is negative. Thus, small firms with lower EV-to-EBIT ratio are more likely to receive a takeover bid. Betzer (2006) and Brar et al. (2009) have also found support for the hypothesis that knowledgeable investors spot firms traded at lower price than their intrinsic value.
- ROA and Asset Turnover ratios proxy efficiency. Negative sign would support the *inefficient management hypothesis.* In line with our expectations, small LBOs are not prone to be driven by the motive to unlock value by replacing incumbent inefficient management. Positive sign of the efficiency proxies shows that small companies that are efficient are more likely to receive a takeover bid. This result is in line with Powell's (1997, 2004) and Nadant and Perdreau's (2011) findings; however, contradicts Betzer's (2006) findings.

- Positive coefficient of the size proxy (Assets) shows that in the small sample larger firms are more likely to be taken over. This rejects the *transaction cost hypothesis.* Thus, potential to save costs related to being listed does not drive small public-to-private transactions. Findings related to the size so far have been very mixed. Our findings relate more to the hostile takeover prediction literature (Nadant and Perdreau, 2011).

Conclusion 4: For small firms, efficient but undervalued firms face higher likelihood of becoming a target for takeover offers. Thus, the motives behind LBOs of smaller firms are mainly related to wealth transfer from pre-transaction shareholders.

Large LBOs

Contrarily to small LBOs, we find that large LBOs are driven by both value creation and value grasping motives. Overall for the large companies, the likelihood of receiving takeover bid increases when ROA and Cash-to-Sales ratio decrease as well as when EBIT-to-Sales and standard deviation of ROIC increase:

- Everything else held constant, we find that large companies with low ROA ratio are more likely to receive a takeover bid. This provides additional support for Betzer‘s (2006) empirical findings that LBOs can be explained by the *inefficient management hypothesis.* On the other hand, positive sign of EBIT-to-Sales ratio contradicts the theory. One potential explanation for this would be that inefficiencies mainly stem from low asset turnover, e.g. too large working capital or fixed assets. This creates improvement potential on a firm’s efficiency and at the same time an opportunity for the private equity firms to earn abnormal returns by taking over the control of the inefficient firm. It shows that motivation for the private equity firms to make a bid for the large company lies in the potential to create value rather than only grasp value as in the case of small LBO bids.

- Cash-to-Sales ratio proxy the *free cash flow hypothesis* that builds on Jensen's principle-agent conflict. Contrarily to the theory; however, in line with the most of the previous empirical studies our findings do not support the hypothesis. Powell (1997) and Brar et al. (2009), for example, also concluded that low liquidity was a shared characteristic among takeover targets.
- The measure of operating risk, i.e. standard deviation of ROIC, proxy the *wealth transfer hypothesis from LPs to GPs*. Positive sign of the coefficient indicates that when it comes to the large companies, operational risk increases the likelihood to receive a takeover bid. This points to the agency-principal conflict of interests within the private equity firms. Once LPs commit their capital to the fund, they do not have a say on the investment opportunities GPs undertake. At the same time, GPs get extra compensated if the fund exceeds the hurdle rate. For GPs, this means that their compensation resembles call-option; thus, volatility increases the value of their compensation. Here we provide the first empirical support for Thorsell's (2013) theoretical proof that GPs always have incentives to increase risk of their fund.

Conclusion 5: For large firms, inefficient firms with low liquidity and high operating risk face higher likelihood of becoming a target for a takeover offers. Thus, the motives behind LBOs of larger firms are related to wealth creation (inefficiency hypothesis) and wealth transfer from LPs to GPs.

The difference in firm characteristics for large and small firms separately could have an implication for the outcome of prediction modeling applied in an investment trading strategy. If an investor applies generic LBO prediction model to calculate the takeover likelihood of a large firm, the results would be misleading. We draw the conclusion that treating large and small firms as one homogenous group will likely lead to higher misclassifications which would affect the outcome of using takeover prediction models as an investment trading strategy.

5.3 Model evaluation

Classification results

Below we present the classification results from the final models using classification rules based on optimal cut-off points (see section 4.7).

Figure 6: Classification table for estimation sample

		Generic	Large	Small
Optimal cut-off point used		*0,243*	*0,355*	*0,636*
Number of firms in total	*A*	248	115	133
Number of actual targets	*B*	81	40	41
Number of predicted targets	*C*	200	45	13
Number of correctly predicted targets	*D*	74	25	10
% Type I errors	*(B-D)/B*	9%	38%	76%
% Type II errors	*(C-D)/(A-B)*	75%	27%	3%
% correct targets of predicted targets	*D/C*	37%	56%	77%
% Prediction accuracy	*(D+A-B-(C-D))/A*	46%	70%	74%
% Random prediction accuracy	*B/A*	33%	35%	31%

The classification rate increases from 46% to 70% and 74% for large and small firms respectively, which is more than twice better than random-based selection criteria.

In previous studies, the Type II errors have commonly been the cause of low portfolio abnormal returns (Hyde, 2009). The impact on portfolio abnormal returns is much greater than type I errors since each wrongly classified target would have a dilutive effect on the overall returns. Hence the proportion of correctly classified targets is a strong determinant of earning abnormal returns in an investment strategy of stock-picking the likely takeover targets (Powell, 2004). Thus, it is noteworthy that the Type II errors decrease significantly compared to the generic model, especially for the small model reporting only type II error of 2%.

According to Palepu (1986), probabilities that are estimated using a state-based sample get overstated since the relation of targets and non-targets is not representative of the true population. The unbiased estimated probability can be calculated using Bayes' formula for conditional probability:

$$p' = \frac{p(n_1/N_1)}{p(n_1/N_1) + (1-p)(n_2/N_2)}$$

where,

p': probability that the firm in the sample is a target
N_1: # of targets in the population
N_2: # non-targets in the population
n_1: # targets in the sample
n_2: # non-targets in the sample

Solving for p, we get:

$$p = p' * \frac{\frac{N_1}{N_1+N_2} * (1 - \frac{n_1}{n_1+n_2})}{\frac{n_1}{n_1+n_2} * \left(1 - \frac{N_1}{N_1+N_2}\right) + p' * (\frac{N_1}{N_1+N_2} - \frac{n_1}{n_1+n_2})}$$

Below we show the unbiased estimates after adjusting for Bayes' formula using the different cut-off points as reference point. The implications are that when our model classifies a firm as a target, the true unbiased takeover probability is 22.1% for large and 22.4% for small firms. According to Palepu (1986), the bias does not change the relative rank of the firms' estimated takeover probabilities.

	Generic	Large	Small
Cut-off point	24,3%	35,5%	63,7%
Unbiased estimate	7,1%	22,1%	22,4%

Detailed calculations of the unbiased probabilities for the models can be seen in Appendix4.

Prediction results

We want to confirm above classification results (existing data) by testing the prediction results (new data) of the model in a holdout sample. The holdout sample was randomly selected as one eight of the estimation sample and consists of 11 targets and 22 non-targets separated into large and small firms (read more in section 4.1). The results from the prediction accuracy are shown in below table.

Figure 7: Prediction table for holdout sample

		Generic	Large	Small
Optimal cut-off point used		*0,243*	*0,355*	*0,636*
Number of firms in total	*A*	33	14	19
Number of actual targets	*B*	11	6	5
Number of predicted targets	*C*	30	5	1
Number of correctly predicted targets	*D*	11	4	1
% Type I errors	*(B-D)/B*	0%	33%	80%
% Type II errors	*(C-D)/(A-B)*	86%	13%	0%
% correct targets of predicted targets	*D/C*	37%	80%	100%
% Prediction accuracy	*(D+A-B-(C-D))/A*	42%	79%	79%
% Random prediction accuracy	*B/A*	33%	43%	26%

In the holdout sample the prediction accuracy almost doubles when large firms are separated from small. There are also significant decreases in type II errors compared to the generic model. The generic model manages to classify all 11 actual targets as targets but also misclassifies 30 non-targets as targets (suffering from over-prediction).

Due to the small sample size in the holdout sample we acknowledge the limitations in the conclusions we can draw from the prediction results in absolute terms. But the relative changes should give as an indication of the improvement in prediction accuracy when large and small firms are accounted for separately. Thus overall, we can conclude that the improvements in the predictions in the holdout sample verify the high improvements in classification rates of the models.

6 Conclusions and Implications

In this section we summarize our research and point out the main findings.

Accurate public-to-private takeover prediction model would enable stock-picking of likely takeover targets before the announcement of the bid. This could be a successful trading strategy on the stock market since stock price of a takeover target tend to increase by 30% after the announcement of the bid (Franks and Harris, 1989).

To construct a successful takeover prediction model, understanding of underlying motives is imperative. At the same time, understanding the drivers of public-to-private transactions is interesting in itself. Although Renneboog and Simons (2005) theoretically explain that the motives depend on the size of the target, currently existing takeover prediction models ignore these differences and treat small and large takeover targets as one homogenous group.

In this thesis, we address this gap in the exiting takeover prediction literature and provide the first empirical support that motives behind small and large LBOs differ. Our empirical results show that the main motive behind LBOs of smaller firms is wealth transfer from the pre-transaction shareholders. Efficient but undervalued firms face higher likelihood of becoming a target for takeover offers. On the other hand, the main motives behind LBOs of larger firms are potential to create value as well as transfer value from LPs to GPs. Contrarily to the small LBOs, inefficient large firms with low liquidity and high operating risk face higher likelihood of becoming a target for takeover offers. The value transfer from LPs to GPs hypothesis so far has not been considered in takeover prediction modeling literature.

These differences in motives between small and large LBOs mean that treating large and small LBOs as a homogenous group and ignoring their differences in takeover prediction models leads to misleading takeover prediction results and low prediction power. Indeed, our empirical findings show that made-to-size models for small and large LBOs have prediction power of 74% and 70% respectively in comparison to 46% prediction accuracy of the model treating small and large LBOs as one group.

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Appendix 1

Year	Authors	Market	Period	Model	No of Targets	Hypothesis	Investment
1973	Stevens	US	1966-70	MDA	40	Tax benefit	n/a
1978	Belkaoui	Canada	1960-68	MDA	25	n/a	n/a
1984	Dietrich & Sorensen	US	1969-73	Binomial logit	46	Undervaluation	n/a
1984	Maupin et al	US	1972-83	MDA	63	Undervaluation, FCF	n/a
1986	Palepu	US	1971-79	Binomial logit	163	Growth-resource imbalance, FCF	Unsuccessful
1990	Barnes	UK	1986-87	MDA	92	Growth-resource imbalance	n/a
1992	Ambrose & Megginson	US	1981-86	Binomial logit	169	Takeover Defense	n/a
1997	Powell	UK	1984-91	Multinomial logit	431	FCF	n/a
1999	Barnes	UK	1991-93	Binomial logit	82	Inefficient management	Unsuccessful
1999	Halpern et al	US	1981-85	Multinomial logit	126	Rejects FCF and incentive alignment	n/a
2001	Powell	UK	1986-95	Binomial logit	442	Focus on investment strategy	Unsuccessful
2004	Nadant & Perdreau	France	1996-02	Binomial logit	175	FCF	n/a
2004	Powell	UK	1986-95	Multinomial logit	471	Growth-resource imbalance	n/a
2006	Betzer	Europe	1996-02	Conditional logit	73	Rejects FCF and agency problem	n/a
2009	Brar et al	Europe	1992-03	Binomial logit	268	Undervaluation	Successful
2009	Hyde	Australia	2000-07	Binomial logit	125	Size and inefficient mngmt least significant	Successful

Appendix 2: Definition Explanatory Variables

<u>Raw variables directly extracted from Datastream</u>

All data is based on a trailing twelve month period if applicable and represents the sum of the relevant item reported in the last twelve months.

Market value: share price multiplied by the number of ordinary shares in issue

Capex: the funds used to acquire fixed assets other than those associated with acquisitions. It includes but is not restricted to: Additions to property, plant and equipment, Investments in machinery and equipment.

EBIT: the earnings of a company before interest expense and income taxes

EBITDA: represent the earnings of a company before interest expense, income taxes and depreciation

Enterprise value: Market Capitalization at fiscal year-end date + Preferred Stock + Minority Interest + Total Debt minus Cash.

EV/EBITDA: enterprise value divided by EBITDA

Free cash flow: sum of Funds from Operations, Funds From/Used for Other Operating Activities and Extraordinary Items.

Book value of equity: common shareholders' investment in a company

Sales: gross sales and other operating revenue less discounts, returns and allowances

Payout ratio: ratio of dividends per share to earnings per share for the last financial period

Total assets: represent the sum of total current assets, long term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets.

Market to book: defined as the market value of the ordinary (common) equity divided by the balance sheet value of the ordinary (common) equity in the company

Return on invested capital: (Net Income – Bottom Line + ((Interest Expense on Debt - Interest Capitalized) * (1-Tax Rate))) / Average of Last Year's and Current Year's (Total Capital + Short Term Debt & Current Portion of Long Term Debt) * 100

Tangible assets: represents the sum of the fixed assets on the balance sheet

Cash and equivalents: represents the sum of cash and short term investments

Total debt: represents all interest bearing and capitalized lease obligations. It is the sum of long and short term debt

Total debt % of common equity: (Long Term Debt + Short Term Debt & Current Portion of Long Term Debt) / Common Equity * 100

Working capital: represents the difference between current assets and current liabilities.

<u>Computed variables</u>

$Capex_t$ / $Sales_t$

$EBIT_t$ / $Sales_t$

Return on assets: $EBIT_t$ / Total $assets_{t-1}$

LogSDROIC: natural logarithm of the standard deviation of ROIC

Free cash $flow_t$ / $Sales_t$

Growth: two-year compounded average growth rate in sales

Growth-resource imbalance (dummy): Value is set to 1 if:
- growth rate is higher (lower) than median estimation sample
- liquidity (cash / sales) is lower (higher) than median) estimation sample
- debt leverage (debt / equity) is higher (lower) than median estimation sample

LogAssets: natural logarithm of total assets

Tangible $assets_t$ /Total $assets_t$

Asset turnover: $Sales_t$ / Total $assets_{t-1}$

$Cash_t$ / $Sales_t$

Net working $capital_t$ / $Sales_t$

Appendix 3

Optimal cut-off probability for large firms

Decile	Cut-off	Targets	Non-targets	Type I Error	Type II Error	% Total Correct	% Targets in portfolio
1	0,0552	114	1	0	74	35,7	35,1
2	0,2247	103	12	0	63	45,2	38,8
3	0,2476	92	23	0	52	54,8	43,5
4	0,2712	81	34	3	44	59,1	45,7
5	0,2969	69	46	6	35	64,4	49,3
6	0,3282	57	58	10	27	67,8	52,6
7	**0,3554**	**45**	**70**	**15**	**20**	**69,6**	**55,6**
8	0,3675	33	82	23	16	66,1	51,5
9	0,3845	21	94	30	11	47,6	47,6
10	0,4219	10	105	35	5	50,0	50,0

Optimal cut-off probability for small firms

Decile	Cut-off	Targets	Non-targets	Type I Error	Type II Error	% Total Correct	% Targets in portfolio
1	0,0907	133	0	0	91	31,6	31,1
2	0,2656	118	15	2	79	39,1	33,1
3	0,3279	104	29	3	66	48,1	36,5
4	0,3717	90	43	5	54	55,6	40,0
5	0,3968	77	56	6	42	63,9	45,5
6	0,4490	64	69	8	31	70,7	51,6
7	0,4940	51	82	11	21	75,9	58,8
8	0,5415	38	95	15	12	79,7	68,4
9	0,5970	25	108	23	7	77,4	72,0
10	**0,6365**	**12**	**121**	**31**	**2**	**75,2**	**83,3**

Appendix 4:

Probability estimates adjusted with Bayes formula

	Generic	Large	Small
Cutoff	*0,243*	*0,355*	*0,637*
True pop	870	200	670
Targets	92	41	51
True targets probability	10,6%	20,5%	7,6%
Unbiased probability	7,1%	22,1%	22,4%

Appendix 5

Relative Influence of the Coefficients

Logit regression model shows which explanatory variables influence the likelihood for a firm to receive a takeover bid. Coefficients also show whether these variables have positive or negative influence on the likelihood. However, the relative sizes of the coefficients do not clearly convey the relative influence of the change in each explanatory variable on the likelihood to receive a takeover bid since the relationship is not linear.

To illustrate what is the relative influence of the change in each explanatory variable on the probability to receive LBO bid, we calculate how the probability changes if one of the ratios increases by 1% from its average ceteris paribus. We use the following formulas to calculate probability to receive a takeover bid when all ratios have mean values. Then, we increase each ratio one-by-one by 1% and in the table below present the difference between the probabilities when the ratio is increased by 1% and the probability when the ratio is not increased.

$$P(Y_i = 1 \mid X_i) = \frac{1}{1 + e^{-X'\beta}}$$

$$X'\beta = \beta_0 + \beta_1 ROA + \beta_2 ATO + \beta_3 OPM + \beta_4 \frac{Cash}{Sales} + \beta_5 \frac{FCF}{Sales} + \beta_6 logA + \beta_7 GRI + \beta_8 \frac{EV}{EBIT} + \beta_9 \frac{N}{E} + \beta_{10} \frac{Tang}{TA} + \beta_{11} logSDROIC$$

Then, we increase each ratio one-by-one by 1% and in the table below present the difference between the probability when the ratio is increased by 1% and the probability when the ratio is not increased. Thus, the difference shows how 1% increase in the ratio from its average value everything else held constant changes the probability to receive LBO bid. It is important to understand that the relationship between the ratios and probability is not linear. This means that marginal influence is not constant. Thus, 1% increase in the ratio from another starting point of the ratio than its average value would give different results. These values, however, are still useful to see the relative importance of the ratios.

Relative influence of the coefficients in generic model

	Average	Coefficient	Change in probability to receive LBO bid in % units if the ratio changes by 1%
ROA	0.05	2.10	0.03%
EVtoEBIT	10.59	-0.05	-0.12%
CashtoSales	0.09	-6.19	-0.12%
LogofAssets	4.98	0.40	0.09%
LogSDROIC	2.35	0.29	0.07%
Constant		-2.32	

Relative influence of the coefficients in the model for small firms

	Average	Coefficient	Change in probability to receive LBO bid in % units if the ratio changes by 1%
ROA	0.06	2.92	0.04%
EVtoEBIT	8.12	-0.06	-0.12%
LogofAssets	4.64	2.02	0.72%
SalestoAssets	1.67	0.54	0.22%
Constant		-10.00	

Relative influence of the coefficients in the model for large firms

	Average	Coefficient	Change in probability to receive LBO bid in % units if the ratio changes by 1%
EBITtoSales	0.06	2.92	0.15%
ROA	8.12	-0.06	-0.15%
CashtoSales	4.64	2.02	-0.21%
LogSDROIC	1.67	0.54	0.20%
Constant		-1.60	

Appendix 6

Wilcoxon signed-rank test verifies assumption that residuals are independent

	Generic	Small	Large
Prob > |z|	0.663	0.481	0.818

Low (VIF<10) Variance Inflation Factor verifies assumption of no or little multicollinearity

	Both	Small	Large
ROA	1.28	1.33	1.49
LogofAssets	1.20	1.22	
EVtoEBIT	1.15	1.17	
LogSDROIC	1.14		1.10
CashtoSales	1.01		1.25
ATO		1.08	
PM			1.61
Mean VIF	1.16	1.2	1.36

Likelihood ratio chi-square test shows that our models are good overall, i.e. our models differ from the 'empty' model

	Generic	Small	Large
Likelihood Ratio chi2	32.18	35.04	21.03
Prob > chi2	0.00	0.00	0.00

Pearson Chi-Square goodness-of-fit test shows that our models fit data well

	Generic	Small	Large
Pearson chi2	227.38	125.85	106.87
Prob > chi2	0.335	0.387	0.326

Hosmer-Lemershow test shows that our models are fitted to all groups of the data

	Generic	Small	Large
Hosmer-Lemeshow chi2	7.61	5.82	9.06
Prob > chi2	0.473	0.667	0.337

Area under Receiver Operating Characteristic (ROC) curve illustrates classification accuracy

	Generic	Small	Large
Area under ROC curve	72%	80%	75%

Appendix 7

Mean value of the ratios for small and large targets as well as control group

Mean	Control group	Small	Large
Total observations	167	41	40
EbittoSales	0,106	0,067	0,158
ROA	0,027	0,061	0,096
EVtoEBIT	12,17	8,125	9,900
FCFtoSales	0,098	0,055	0,108
CashtoSales	0,102	0,074	0,072
GRI	0,257	0,268	0,375
LogofAssets	4,829	4,631	5,646
TangAssTotAss	0,506	0,458	0,388
SalestoAssets	1,184	1,658	1,200
NetDebttoEquity	0,366	0,488	0,882
LogSDROIC	1,334	2,395	2,495

Appendix 8

Regression results with rescaled data to see if the results are not influenced by cross-sectional time variation.

MODEL FOR SMALL AND LARGE	
Number of obs	233
Likelihood Ratio	30.13
p-value	0.00
Pseudo R^2	0.10

	Coef.	Std. Err.	P>|z|	Odds Ratio	Prob.
ROA	1.77	0.91	0.05	5.89	0.15
EVtoEBIT	-0.28	0.13	0.04	0.76	0.57
CashtoSales	0.43	0.17	0.01	1.54	0.39
LogofAssets	-5.98	1.93	0.00	0.00	1.00
LogSDROIC	0.28	0.14	0.05	1.32	0.43
Constant	-0.66	0.45	0.14	0.52	0.66

MODEL FOR SMALL	
Number of obs	131
Likelihood Ratio	27.11
p-value	0.00
Pseudo R^2	0.17

	Coef.	Std. Err.	P>|z|	Odds Ratio	Prob.
ROA	2.16	1.33	0.11	8.68	0.10
EVtoEBIT	-0.37	0.19	0.04	0.69	0.59
LogofAssets	1.43	0.44	0.00	4.19	0.19
SalestoAssets	0.25	0.13	0.06	1.29	0.44
Constant	-0.62	0.39	0.11	0.54	0.65

MODEL FOR LARGE	
Number of obs	107
Likelihood Ratio	16.98
p-value	0.00
Pseudo R^2	0.12

	Coef.	Std. Err.	P>|z|	Odds Ratio	Prob.
CashtoSales	-8.54	3.22	0.01	0.00	1.00
SalestoAssets	-0.31	0.18	0.08	0.73	0.58
LogSDROIC	0.79	0.27	0.00	2.20	0.31
Constant	-1.01	0.69	0.14	0.36	0.73