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Can LBOs in the U.S. Manufacturing Industry Be Predicted Using Financial Ratios?

A Logit Model Approach

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In acquisition prediction modeling, taking into account the relationship between target and acquirer as well as correctly establishing the holdout sample seems to have implications for the results. In a Logit model, using a sample of Private Equity initiated LBO transactions in the U.S. Manufacturing Industry 1997-2006, accounting for survivorship bias in the calibration sample (and hold-out sample) as well as using industry relative ratios; we correctly classify 97.5 percent of the companies in a multiyear hold-out sample and achieve a positive predictive value of 57.69 percent. Receivables to Payables, and Size are found to be the most explanatory factors, where Receivables to Payables is a new ratio in acquisition prediction modeling. Further, some support for the Control Hypothesis is found.

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Introduction

Takeover prediction modeling is not a new topic and ever since the second half of the 20th century economic researchers have calibrated statistical models to deduce potential determinants of acquisition likelihood. If a model succeeds in correctly predicting companies that will be acquired, a trading strategy can be formed in order to earn abnormal returns on the bid premiums (Powell, 2004). Even though researchers have debated and tested most statistical methods and proxies, the predictive ability of their models are inadequate. As pointed out by Powell (1997), problems with many earlier studies are that they try to quantify multiple specific takeover theories based on a sample of several kinds of transactions. The results become inconclusive since different theories can be valid or rejected for different types of acquisition targets.

Previous studies (e.g. Palepu, (1986), Barnes, (1999), and Powell (1997)) generally use a naïve holdout sample to test their model's predictive ability, where the hold-out sample either is based on observations from a single year, or suffers from a survivorship bias.

Trying to fit a large picture into a small frame is per definition a fool's errand. We believe that in order to end up with statistical results worth interpreting, the characteristics of a financial transaction must be mapped using a quantitative setting that accounts for the target's and acquirer's relationship in a joint manner. The method to investigate this can be illustrated as a sliding tradeoff scale, where studying all acquisition types jointly is positioned on the left hand side and a specific case study of a single transaction on the other. The tradeoff in turn translates into a scale between rough general conclusions and specific analysis. Keeping the tradeoff in mind, we have chosen LBO transactions in the U.S. manufacturing industry during the period 1997-2006. By limiting our sample to LBO transactions by PE investors in the manufacturing industry, we replicate a setting that accounts for the relationship between the target and the acquirer.

The primary focus on this thesis is to investigate if taking into account the relationship between the target and the acquirer, improves acquisition takeover modeling from an investors point of view. Additionally some methodological choices within the takeover prediction literature are discussed.

Predicting Private Equity acquisition targets in the manufacturing industry in the U.S. by the use of a statistical Logit model we achieve a prediction value in a multiyear hold-out sample of 97.5 percent and are able to classify 57.69 percent of the targets correctly. The importance of taking into account survivorship bias in the holdout sample seems to improve predictive ability of the model.

The main benefit of looking at LBO transactions done by PE investors is that we manage to eliminate the error influenced by strategic acquisitions, which are not considered in earlier studies. Assuming PE investors in LBO transactions have a consistent investment strategy, a relationship between accounting data and acquisition propensity should be possible to establish. By constructing our model on manufacturing companies, we expect the data points to be of better quality in terms of comparison. Using all industries results in errors inherited from a bias in industry specific accounting treatments (Powell, 2004).

Further, our thesis is based on a later time period than earlier research.

Delimitations

We refer to leveraged buy-out (LBO), management buy-out (MBO), management buy-in (MBI) and institutional buy-out (IBO) jointly as LBO. If management is the initiator of the transaction it is generally called an MBO, alternatively if the LBO is initiated by an external management it is denoted MBI. The firm acquired will be referred to as the target company and the acquirer as the private equity (PE) investor. If the acquiring entity is an investment consortium lead by a PE firm with more than a 50 percent majority, we will refer to the acquirer as a PE investor or PE firm.

The LBO firms refer to themselves (and are generally referred to) as PE firms (Kaplan and Strömberg, 2008).

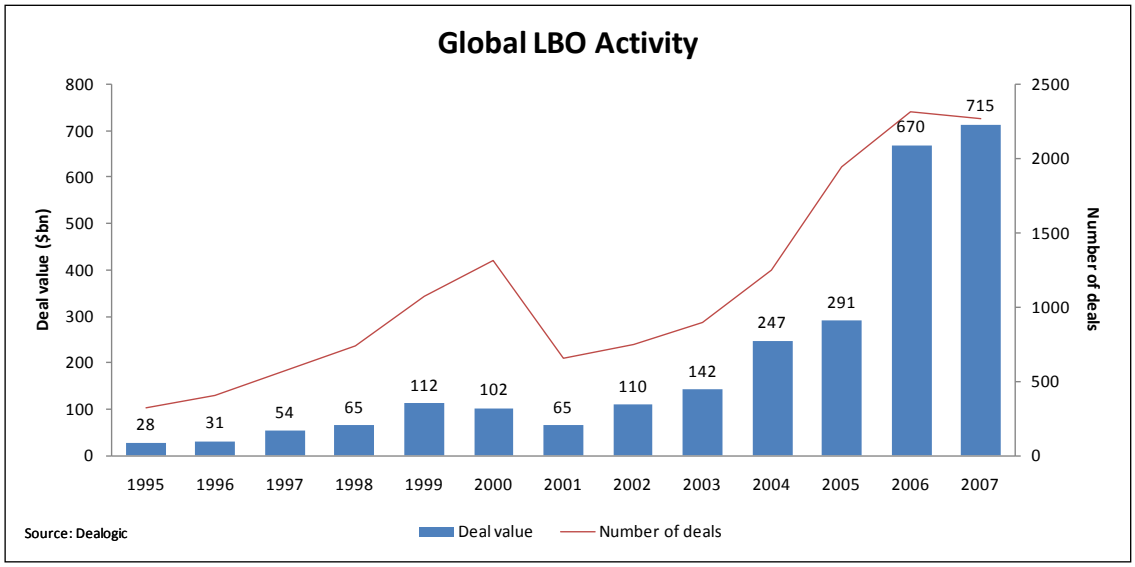
In an LBO transaction a controlling stake is bought by a PE investor. The difference from non-leveraged transactions is that the amount of debt used to finance the transaction in terms of purchasing price; refinancing and transaction costs are more than 50 percent. The required equity is supplied by the PE investor and potentially to a smaller part by the target company or division management team (Halpern et al. 1999). In an LBO, assets of the target company are usually pledged as collateral for the debt to be issued in the transaction (Bergman and Bergman, 2006).

Background

The private equity (PE) dimension referred to as the LBO phenomena started in the U.S. during the mid ‘70s. The amount of capital committed in PE funds and the size of the aggregate investments has been growing ever since. The development of the industry has been cyclical and have had different periods of strong growth succeeded by periods of modest volumes and absolute declines in value (Kaplan and Strömberg, 2008). This volatile trend over time is described by two different LBO waves that have had different triggers and characteristics.

The two waves of PE development can be further divided into four sub periods. In the first period 1974-1984 it was a newborn industry with small firm executing small deals that were not important to the rest of the financial world. The new innovation of debt financing instruments was starting to be used. In the second period 1985-1990 more firms adopted the PE approach with committed capital from a wider investor base and debt financing became more common as the usage of junk bonds appeared. Throughout this period public companies started to be taken private to a larger extent. During the third period 1991-2001 the PE funds had grown to multi-billion dollar funds having global investors and lenders and many new funds were raised. Pension funds were the dominant investor. In the current fourth period, PE activity has become a global business where 175 funds have more than $1bn under management. Fortune 500 companies going private and LBOs accounted for roughly 40 percent of M&A transactions in 2007. Today PE firms have started to list themselves on the exchange and the public/governmental inspection is increasing (Gottschalg, 2008).

Table 1: Global LBO Activity [1]



Development in North America

The LBO business model, executed by PE firms, started in the mid '70s and small transactions were executed by small firms and were of no significance to the rest of the financial world, but the innovations of debt financing created during this period laid the foundation of what is today a global business (Gottschalg, 2008). A wider investor base appeared in the U.S. during the early '80s and until today the amount of committed capital in U.S. PE funds have grown from roughly $0.2bn in 1980 to $200bn in the end of 2007. Adjusted to real buying power this corresponds to approximately one percent of the total U.S. stock market capitalization in 2007 (Kaplan and Strömberg, 2008).

Estimations illustrate that in the '80s, 57 percent of all listed companies in the U.S. were hostilely taken over or restructured (Mitchell and Mulherin, 1996). Since some mergers did not go through and excess capacity was built up, the Merger and Acquisition (M&A) wave boosted LBO activity (Jensen, 1991). 26.3 percent of all takeover activity 1981-1984 was in the Oil and gas industry (Jensen, 1988). The trend was not restricted to smaller firms anymore, but also incorporated large firms, e.g. the LBO fund KKR's[2] buyout of RJR Nabisco in 1989 (Renneboog and Simons, 2005). When the LBO phenomena gained momentum and debt financed transactions became more mainstream in the end of the 80s, it was predicted that LBO funds would become dominant as a corporate governance solution, based on the idea that PE firms has the characteristics of an efficient organization with a solid ownership structure, aligned with management incentive systems and low overhead costs. By active governance the PE investors managed to increase leverage and introduce more efficient incentive systems in the companies. Such an investment approach was considered to be superior to typical structures in public companies with a scattered ownership base, weak governance, and low leverage (Jensen, 1989).

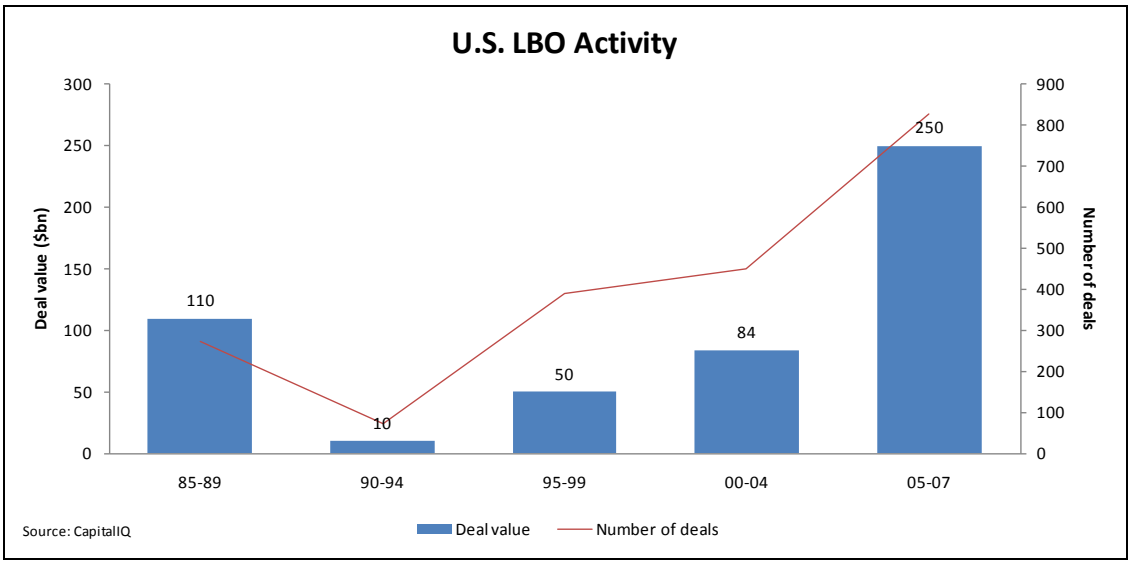
[1] Data is originally collected from Dealogic and later summarized by professor Gottschalg at HEC Paris in CEMS Program Fall 2008

[2] Kohlberg, Kravis and Roberts

The LBO wave in the '80s was attributed many bankruptcies, resulting in public and political opposition (Shleifer and Vishny 1991). The Anti-takeover legislation, public leverage constraint and credit crisis originating from the crash of the junk bond market more or less ended the first LBO wave in the early '90s. But even if the public-to-private transactions by LBO firms disappeared, the LBO activity itself only altered form and until the early '00s, the LBO firms mainly acquired non listed firms and divisions (Kaplan and Strömberg, 2008).

The second LBO wave was triggered in the late '90s to early '00s by small companies with a low trading volume that suffered from threat of being delisted from NASDAQ together with increased costs of listing due to the Sarbanes-Oxley Act. Consequently the option of going private seemed even more attractive (Kaplan and Strömberg, 2008).

Table 2: U.S. LBO activity expressed in Enterprise value[3]



The trends in U.S. were early adopted and closely followed by the UK economy, though smaller in terms of aggregate transaction value. The main trigger of the second wave in the late '90s in the UK however differed from that in the U.S. Reasons for the second wave were that investors experienced increased information transparency in terms of due diligence, more supportive managements and shareholders, and the possibility to get hold of all shares in a bid using the minority squeeze out regulations[4] (Ashurst et. al, 2002).

Continental Europe's LBO activity has been lagging behind the UK as PE investors generally deem transactions in continental Europe to be more risky and costly. There is another culture in continental Europe, where companies view delisting as a failure and are proud if manage to

[3] Transactions include all PE deals in the CapitalIQ database between 1985/01/01 and 2007/06/30. Transaction value is Enterprise value defined as the sum of net debt and equity used to finance the transaction using dollar currency of 2007. For the transactions where enterprise value was not recorded, values have been computed by Strömberg (2008).

[4] The UK Companies Act states that if acquiring 90 percent of the shares, the remaining minority can be forced to sell

remain listed. PE investors also tend to be more uncertain about their possibilities to exit their investment during economic downturns in the non UK markets. Further, investors were not able to use the squeeze out provisions as freely as in the UK (Renneboog and Simons, 2005).[5]

Theoretical Framework

The reasons for LBOs have been widely discussed and grouped into eight main hypotheses (Renneboog and Simons, 2005). The following framework lays a foundation for understanding the forces that drive an LBO decision.

(1) Tax Benefit Hypothesis

The Tax Benefit Hypothesis declares that wealth creation in LBOs originates from tax benefits of interest deductions due to an increase in debt as funding source (Renneboog and Simons, 2005). A LBO transaction increases the target debt portion of the capital structure, with a related increase of tax shields due to an increase in interest payments, thus a source of value creation according to financial text book theory (Brealey et al., 2005). The amount of value creation that can be obtained consequently differs depending on the characteristics of the tax regime. Estimates show that during 1980-1986 the median value of tax shields constitutes 21-148 percent of the premium paid to shareholders in LBO transactions (Kaplan, 1989b).

(2) Incentive Realignment Hypothesis

The Incentive Realignment Hypothesis explains that value is derived from an increased concentration of ownership and control due to the LBO transaction (Renneboog and Simons, 2005). As management is given a larger equity stake in the target company, value is created by aligning interests between management and shareholders, reducing the risks of managers only investing in projects with a positive net present value and instead focuses on value creating measures, such as increasing operational activities and restructuring assets. The potential downside is that this may lead to underinvestment (Lundgren and Norberg, 2006). The median increase in management equity stake was between 4.41-9.96 percent (Kaplan, 1989a).

(3) Control Hypothesis

The Control Hypothesis implies that value is created as a consequence from increased ownership quality (Renneboog and Simons, 2005). Public firms may have a wide ownership base and via an LBO the shareholder base becomes more concentrated. Value is created by reducing the "free rider" investors and change to an increased ownership quality, as professional and active investors will monitor the target company more efficiently. At the same time the shareholders can no longer sell their shares on the capital markets, thus having increased incentives to improve the target company (Lundgren and Norberg, 2006).

(4) Free Cash Flow Hypothesis

The Free Cash Flow Hypothesis states that value creation in an LBO is an effect from removing free cash flow conflicts (Renneboog and Simons, 2005). Free cash flow is defined as "cash flow in excess of that required to fund all projects that have positive net present value when discounted at a relevant cost of capital" (Jensen, 1986). The conflict between owners and

[5] For data on European LBO activity, see appendix table A and B

management arises from how to manage the excess cash flows in an efficient manner, i.e. to pay out excess funds as opposed to investing it in projects with a return below the required cost of capital or wasting it on operational inefficiencies, as exemplified by the U.S. oil industry in 1970s. Taking up new debt signals to shareholders that managers promise to pay out future cash flows as a substitute to dividends, thus reducing agency costs in the organization since management may have to operate more efficiently to avoid bankruptcy (Jensen, 1986).

(5) Wealth Transfer Hypothesis

The Wealth Transfer Hypothesis advocates that value in an LBO transaction comes from shifting value away between stakeholders. Wealth can be transferred from debtors to shareholders by increasing the risk in projects taken on, substantially increase the dividend payout or issue new debt of higher seniority. Studies are two-folded when it comes to showing that bond holders lose value in an LBO transaction. One noticeable conclusion is that value destruction tends to hit bond holders with covenants of low protection, which in turn indicates that former bondholders do not lose value, but rather missing out on recovery not originally contracted for. Value could also be shifted from employees to shareholders, because an LBO transaction can break official or unofficial contracts with employees and suppliers, e.g. reducing number of employees or wages (Renneboog and Simons, 2005).

(6) Transaction Costs Hypothesis

The Transaction Costs Hypothesis states that value in an LBO transaction originate from reduced listing costs of the stock exchange (Renneboog and Simons, 2005). Studies on this area specify that costs incurred by a U.S. listed company is approximately $0.1mm annually, corresponding to $1mm if capitalized with a 10 percent discount rate (DeAngelo et al., 1984). Estimations in the UK including costs for fees to e.g. stockbrokers, lawyers, bankers and PR firms indicate an annual cost of £0.25mm (Benoit 1999). CEO's have further estimated these costs to be up to £0.5mm (Renneboog and Simons, 2005).

(7) Takeover Defense Hypothesis

The Takeover Defense Hypothesis suggests that value created in an LBO transaction is due to management's interest to take increased control of the target company (Renneboog and Simons, 2005). It is argued that LBO transactions are used as a final way of avoiding a hostile takeover and management is afraid of losing their jobs in case of such an event (Michel and Shaked, 1986).

(8) Undervaluation Hypothesis

The Undervaluation Hypothesis states that through an LBO transaction the target company's assets can be valued higher if used in alternative ways. If a company was described as a collection of assets, there might be an information bias between the market and the managers, as managers would know that the future returns on the asset portfolio in fact is higher than what is expected from the external stakeholders. Consequently, understanding that the share price is lower than what is motivated by the fundamentals, would give reasons to execute an LBO transaction (Renneboog and Simons, 2005).

Prior Research

The studies made on acquisition modeling take off in the theoretical framework and seek to test if any, some or all of the eight hypotheses can be validated using a selected set of variables as proxies. Earlier research on the subject is not exclusively directed towards LBO transactions, and includes acquisition models on all kind of transactions.

Even if research differs in what type of transactions that are selected for further study, the hypotheses used are ultimately the same, even if some authors e.g. Palepu (1986) defines his hypothesis slightly differently. The Free Cash Flow and Undervaluation Hypothesis have been widely elaborated on. There is not a clear view on whether the Free Cash Flow Hypothesis generally can be validated, even if the difference between studies based on MBO data or acquisition targets in general are considered. The second most commonly discussed explanation for acquisitions is the Undervaluation Hypothesis, which is accepted by the general consensus. Further, the Tax Benefit Hypothesis is frequently accepted. Finally, there has been statistical proof supporting the Wealth Transfer and Takeover Defense Hypotheses, while the Incentive Realignment Hypothesis has not been shown to be of significance.

Much effort has been put in to adjusting the statistical methods in order to validate the above hypotheses. Such discussions are guided by e.g. Palepu (1986), Barnes (1990) and Powell (1997, 2004). They are the strongest advocators for the choice of statistical method. Their view is that due to the models inability to predict results on a satisfactory level, no hypotheses can ultimately be accepted or rejected. A suggested solution is to take the relationship between target and acquirer into account, since much of the financial characteristics of the transaction originates from that relationship (Powell, 1997).

North American Results

Belkoui (1978) finds in a sample of 25 Canadian target companies during the period 1960-68 that an 85 percent classification rate can be obtained after adjusting cut-off values using a dichotomous test. Non-liquid ratios are the best in terms of predicting power, specifically Working Capital to Total Assets. Data indicated that accounting ratios were better in prediction power, two or three years prior to an acquisition. Since the sample used was limited to small companies it is inconclusive which theoretical hypothesis that is valid.

Stevens (1973) shows similar predictive abilities in his model constructed on 40 U.S. acquisitions made in 1966, with a control period of 1966-70 making sure that no company was later acquired. Using a discriminant function based on Long Term Liabilities to Assets, EBIT to Sales, Net Working Capital to Assets and Sales to Assets, he demonstrates a correct classification prediction of 70 percent. His findings show that financial characteristics can be used in order to separate targets and non targets in which capital structure is important both on a standalone basis and in combination with liquidity, profitability and activity. Stevens (1973) does not elaborate on which hypothesis this would support, but from our perspective his work seems to support the Tax Benefit Hypothesis, i.e. the tax benefits originating from increased interest payment deductions.

Dietrich and Sorensen (1984) get comparable results for their 46 U.S. targets in the period 1969-73. Using a logistic regression they get a 90 percent accuracy, concluding that low sales per asset is an important factor for targets and that low turnover must be in combination with all or any of low payout, low leverage, high trading volume or a relative small size. We interpret this as supportive for the Undervaluation Hypothesis as incumbent management fail to generate sufficient return on their assets.

Maupin, Bidwell and Ortegren (1984) choose to look at 63 U.S. MBO transactions in the period 1972-83 and see if it is possible to separate MBO targets from those who remain public. Using a discriminant analysis the conclusion is that MBO targets generally have a higher management ownership concentration, contradicting the Incentive Realignment Hypothesis. However, they find somewhat uncertain proof for the free cash flow and Undervaluation Hypothesis. Likewise, Kieschnick (1989) uses data from 102 MBOs in the period 1981-85 and conclude that undervaluation is a strong explanation of MBOs and imply that the tax benefits could not be the reason since the gains are obtainable for any other buyer. Lehn and Poulsen (1989) oppose Kieschnick (1989) using a logistic regression on a sample of 244 going private transactions 1980-1987. Their results indicate that companies go private when there is likelihood of hostile bids, thus supporting the Takeover Defense Hypothesis. They are also in favor for the validity of the Free Cash Flow Hypothesis. Kieschnick (1998) revisits Lehn and Poulsen (1989)'s study implementing suggested adjustments and finds support for tax shields and size, but rejects the Free Cash Flow Hypothesis.

Kaplan (1989b) focus on a more specific subject and tests the Tax Benefit Hypothesis by analyzing data 1980-85 for 76 MBOs on the U.S. market. His findings indicate that tax benefits are a source of capital gain in MBOs and illustrate that approximately 76 percent of the tax shield is paid out to sellers, corresponding to 21-72 percent of the premiums paid by the acquirers. Kaplan (1989b) further notes that the value of tax shields could be accessible without going private.

Palepu (1986) looks at earlier predictive model research and argues that they have inherited a couple of fundamental flaws and tests if the predictive power of these models still can be obtained if correctly adjusted. The three main defects are (1) non adjusted state-based samples distorts the probability estimations (2) wrong proportion of samples to the population gives wrong estimates and will most likely overstate the models prediction ability (3) arbitrary cut-off values chosen without decision rules impedes the interpretation.

By adjusting for these errors Palepu (1986) constructs a nine variable Logit model based on (1) average excess returns (AER) for the share price, (2) Growth Resources Mismatch Dummy, (3) Growth in Sales, (4) Liquidity, (5) Leverage, (6) Economic Disturbance Dummy, adjusting for industry shocks, (7) Size, (8) Market-to-Book, (9) Price-to-Earnings, (P/E), and (10) industry dummy, for the period 1971-79 using a sample size of 163 targets and 256 non targets. The industries are limited to mining and manufacturing. Using a hold-out sample of 30 targets and 1,087 non targets, the model found 24 of those 30 targets, however with a setback in term on the amount of misclassifications of non targets, adding up to a 45 percent correct classification rate and concluding that prediction models fail to generate abnormal returns. The result of the study does not support any of his tested hypotheses.

Ambrose and Megginson (1992) investigate data between 1981-86 for 169 targets and 267 non targets to a takeover bid. They use a model similar to Palepu (1986), with modifications to incorporate institutional and insider ownership, takeover defenses and portion of tangible assets of the total asset pool. Their study shows fairly low significance, but they conclude that there is a relationship between targets and defense measures.

Opler and Titman (1993) investigate how bankruptcy risk influences the decision of performing an LBO transaction. They conclude that companies that execute an LBO transaction generally have a mixture of low growth opportunities and strong free cash flows, thus validating the Free Cash Flow Hypothesis. Their data also support that LBO targets are more diversified operationally. Firms with potentially high cost of default, e.g. R&D costs or are in the manufacturing of machines and equipment industry are less likely to perform LBOs.

Kim and Arbel (1998) study the hospitality industry specifically. Using a binomial Logit model on 69 hospitality targets 1980-92 they find that Market-to-Book, Growth Resource Imbalance and the level of CAPEX in relation to assets are of high significance. They find that firms of larger size are more likely to be acquired, and note that this can be due to industry specific characteristics.

Halpern, Kieschnick and Rotenberg (1999) study the period of 1981-85 for 126 MBOs and focus on management ownership by dividing the sample into two sub groups. One group represents those with low concentration, and the other those with high concentration of management ownership before the MBO. They find that the first group has lower leverage than a control sample of listed companies, and that the other group has higher leverage and worse stock price performance. Conclusively the study illustrates a positive relationship between MBOs and managerial ownership levels, thus inconsistent with the Incentive Realignment Hypothesis. For both subgroups the Free Cash Flow Hypothesis is discarded.

European Results

Barnes (1990) methodologically continues where Palepu (1986) ended, by using a multiple discriminant analysis (MDA) and industry relative ratios to achieve a more time consistent model. He uses a sample of 92 UK targets for the period 1986-87. When incorporating (1) Quick Assets to Current Liabilities, (2) Current Assets to Current Liabilities, (3) EBT to Sales, (4) Net Income to Sales, and (5) Return on Equity, the model manages to classify 68 percent of the targets and further by using a new sample of 37 targets matched to 37 non targets the model ends up classifying 74 percent of the targets correctly, although not adjusting according to the suggestions from Palepu (1986). Further, Barnes (1999) finds that the choice of industry relative ratios versus raw financial data has negligible impact on the result. He suggests that the choice of cut-off values should be chosen to maximize the potential profit for an investor. Even if his models have a high classification rate they are unable to differentiate targets from non targets regardless of cut-off value. However, Barnes (2000) further investigates if there is a potential difference between discriminant models and Logit models, and how industry relative ratios versus raw financial data impact the results. He finds that the Logit model with industry relative ratios performs better in acquisition takeover modeling.

Powell (1997) tests if there is a difference between hostile and friendly bids on transactions in UK 1984-91 on a sample consisting of 431 targets of which 97 are hostile and 334 friendly. Hostile bids are defined as when management rejects the first bid, though noting that this can

result in bias depending on the intentions of the rejection. The total sample is then divided into two sub periods 1984-87 and 1988-91. The variables tested are (1) ROCE, (2) Log of Total Assets, (3) Tangible Fixed Assets to Total Assets, (4) Market-to-Book, (5) Growth in Sales, (6) Cash and Marketable Securities to Total Assets, and (7) Leverage. Thomas (2003) criticizes Powell (1997) for his definition of hostile targets, and suggests that hostility is better defined with respect to changes in top management instead.

Powell (1997) finds that there is a significant difference in characteristics between the two target groups. Further he finds that binomial models that treat friendly and hostile targets as one group of targets are likely to produce unsatisfying results, as opposed to multinomial models that are more accurate when predicting takeover events. Results also indicate that both firm specific and industry specific properties affect takeover likelihood. Powell (1997) further points out that since there are differences in the characteristics of the target firms between the periods the result is inconclusive to which parameters that will correctly predict acquisition events in both periods. The broad range of theories explaining takeover events could all be true for some targets, but in the end does not support building a trading strategy due to the low explanatory power in the models, adding that the relation between target and acquirer could be focus for research and at this point the main source of disturbance.

Powell (2004) further investigates if the use of industry relative ratios (IRR) improves the models explanation power and if it is possible to earn abnormal returns. Using a multinomial Logit approach with IRR on UK data, consisting of 471 targets in which 81 are defined as hostile and 390 as friendly, Powell (2004) shows a difference between hostile and friendly targets, attributed primarily to size. Using a multivariate model has a higher significance and explanatory power as well as a higher correct classification rate of 75 percent. Further Powell (2004) discovers that an abnormal return of approximately 7 percent on a portfolio of predicted hostile targets is possible.

Nadant and Perdreau (2004) use a Logit regression and investigate if any differences can be found between LBO targets and non targets in France 1996-02 using a sample of 175 targets that are matched to a non target. The variables tested are free cash flows, taxes, capital intensity, business risk, profitability, capital structure and type of assets. Their study confirms that LBO targets have lower leverage and more liquid assets than their matched non target and indicates that the Free Cash Flow Hypothesis to some extent is valid. LBO targets generally exhibit a more risky profile than those that remain public. When dividing the target sample after type of seller, independent targets are smaller, show a higher profitability and higher EBT opposed to divisional divestures, which generally are less profitable and have relatively more financial assets than their control companies. However, no difference between MBOs and IBOs is found.

Method

The method we have used to calibrate and evaluate the Logit model will be described, we will thereafter more extensively discuss some trickier methodological issues. The methodological issues we choose to further elaborate on is the choice of econometric model, sampling method, variable selection, time inconsistence, cut-off points and model estimation. The handling of the survivorship bias is discussed at length.

Sample Description

The list of U.S. deals is extracted from the Zephyr database for the period 1997/01/01-2006/12/31. The reasons for choosing this time period are:

1. Zephyr's first data point is from 1997
2. The first LBO wave was approximately ten years, and we therefore match the time period
3. A company can be a target in 2007, and we want to be able to control for that fact.

We look at companies in the manufacturing industry. The manufacturing industry is defined as SIC codes in the interval 2000-3999 (Hall, 1990). We exclude SIC code 283x; Pharmaceutical Manufacturers and Sales, because the pharmaceutical industry has a lot of intangible assets, which could distort several of our ratios. We extract all companies defined within the given industry with: (1) an acquired ownership stake above 50 percent (including unknown stake) within (2) all deal types and (3) the financing being "LBO" or "PE". An above 50 percent hurdle is used because that there are no squeeze-out provisions in the U.S., and over 50 percent is sufficient to take a company private in some states, even though 66.67 percent is required in other states (DeAngelo 1984). We identify 1,513 potential targets. Of these, 22 targets are not American and are thus excluded. As our purpose is to identify PE buyouts from the stock-exchange and since Zephyr's reported data whether or not a company has been listed and/or the acquirer are really a PE firm is insufficient, we need to cross-reference the extracted target list with the information in the DataStream database (Worldscope) in two rounds. In the first round we manually look up all stated PE buyouts row by row, to match/find their stock ticker code in order to see if they actually were listed at the time of the buyout. In the second step we investigate if the stated acquirer is really a PE firm or a PE firm consortium, by reading deal details on the PE websites or in articles published in the Dow Jones Factiva database. This procedure reduces the sample to 280 targets from our initial sample size of 1,513.

To get a list of non targets, we search for all companies that have ever been listed on the OTC Bulletin Board, Nasdaq or NYSEX (active, dead on suspended) in DataStream within the categories Beverages, Chemicals, Construction and Materials, Electronics & Electronic Equipment, Food Producers, Forestry & Paper, Household Goods & Home Construction, Health Care Equipment and Services, General Industrials, Gas, Water & Multiutilities, Industrial Metals and Mining, Industrial Engineering, Mining, Oil and Gas Producers, Tobacco, Technology Hardware and Equipment and Personal Goods. We then lookup the primary SIC code for these companies to get a sample of the companies that have been/are listed in the U.S. during this time period. This produces 2,329 non-target companies, giving us a total population of 2,609. The total population is 15,517 if each year's observation is counted as one data point. This population will be referred to as the population going forward.

Accounting data is extracted from DataStream and the ratios are calculated (see table C in appendix). Visual inspection of the sample shows several companies absent of data points or with odd data points. Outliers are defined as values more than three interquartile ranges (IQR) from the 1st and 3rd quartile values. These outliers are winsorized back to three times IQR from the 1st and 3rd quartile value, in order to retain as much data as possible in the sample.[6] We then calculate the average for each variable and divide each data point with the corresponding year's

[6] For a complete view of number of data points winsorized back per ratio, please see table D in appendix

average. This is done to make the input in the model more time consistent.[7] To be included in the sample the company needs at least three years of data.[8] This reduces the total number of companies to 1,599 of which 128 are targets. None of the 1,599 companies became targets in 2007.

Econometric Model

We have chosen to use the Logit model in this thesis. The Logit model is the case where:

$$G(z) = \Lambda(z) \equiv \frac{\exp(z)}{1+\exp(z)} \ , \ z = \alpha + \sum_{i=1}^{n} \beta_i x_i$$

This means that that the probability of outcome 1 (the company is a target) is given by the estimated *alpha* and *beta* coefficients as well as the observed *independent* variables. The independent variables have a linear relation to the log quota of the two observed probabilities. The choice of econometric model will impact the final results and there is a tradeoff between different models. Earlier studies use three different econometric models; Logit, Probit and Multiple Discriminant Analysis (MDA) (inter alios Palepu, (1986), Harris et al., (1982) and Barnes, (1990)). Both the Logit and the Probit models are binominal index models, using the form:

$$(1) \ P(y = 1|x) = G(x\beta) \equiv p(x)$$

If G is a cumulative distribution function (CDF), then the formula above becomes the latent model:

$$(2) \ y^* = x\beta e \text{ and } y = 1[y^* > 0]$$

Logit and Probit models are called index models as they restrict the way that the probability *p* depends on *x* as they depends on *x* only through the index of *x*. The Logit and Probit models follows the CDF, with the difference that Probit uses the CDF of the normal distribution and Logit the logistic CDF i.e. the error term e is either normally distributed or follows a standard logistic distribution (see further Wooldridge, 2002). The choice between Logic and Probit is more a matter of taste as it can be shown that the models give similar result, but statistically the Probit models have fatter tails (Gujarati, 2003).

MDA is another option used in several other studies. The main drawback of MDA is that it requires the sample data to be multivariate normally distributed. MDA may also hide troublesome data as the estimators may provide a perfect fit even if that is not the true case (Barnes, 2000). We therefore decide not to use MDA. The requirements on the data in the Logit model suit our dataset better.

The assumptions to use the Logit model are not that strict, and are stated below.

- The observations are assumed to be randomly sampled
- Y is caused by or associated with the X's, and the X's are not determined by other X's
- There is uncertainty in the relation between Y and the X's (Christensen, 1990)

It is rather evident that there is an uncertainty between the Y and X's in our data sample, the two other requirements might be violated, e.g. because we use accounting data the X's could be

[7] See further chapter Time inconsistency problem

[8] 3 years of data is required to calculate the variable 2 years average sales growth.

argued are determined by other X's. We also have to make sure that the observations are randomly sampled. These requirements will therefore be examined further.

Sampling Method

There are two main sampling methods; (1) random, and (2) stratified. The requirement as stated above in the Logit model is that the observations are randomly sampled, but that includes stratified sampling. In (1) random sampling the observations are drawn at random from the full population, which is not recommendable in our case as the number of targets in the estimation sample might turn out to be too few in order to deduce meaningful data. In (2) stratified sampling, the population is grouped into several subsets based on some exogenous or endogenous variable. The estimation sample is then drawn from the different subgroups. A stratified sampling based on endogenous variables are called a choice based sampling (Cosslett, 1981).

We choose to use choice based sampling as we divide our population in a target and a non-target group, and then extract a random sample. The reason for choosing choice based sampling is that we in a pure random sampling might have trouble to sample enough targets to get any information from our dataset. This will give a bias in the modeling as the maximum likelihood method used in the Logit model assumes true population ratios (Palepu, 1986). Palepu (1986) shows that the bias can be adjusted by using Bayes' formula, which we will use to adjust the bias due to the sampling characteristics. To ensure a random sampling, all targets are formed into a group of companies and given a random number between 0 and 1. If the random number takes a value below 0.66, the target is included in the estimation sample.

As the matched company needs to have data available for the same year as the target, i.e. be a listed company at the time, each non-target company is grouped into yearly sub-groups. A non-target company can be included several years, if they have data for several years. We believe this procedure to be a better way to construct the population, since we otherwise would introduce a survivorship bias that neglects that a company which is present in the population over the whole time period is more likely to be chosen (Powell, 1997). Each observation is then assigned a random number between 0 and 1 and the data is sorted from the highest random number to the lowest. The non-target group is then matched to the target group by acquisition year and random number. The non-target companies with the highest random-number for that year are chosen as the matched company given that it has not been matched to another target. This ensures that companies with multiple observations have a higher likelihood to be chosen. 88 targets and 88 non targets are chosen to be included in the estimation sample, leaving 40 targets in the holdout sample.

Variable Selection

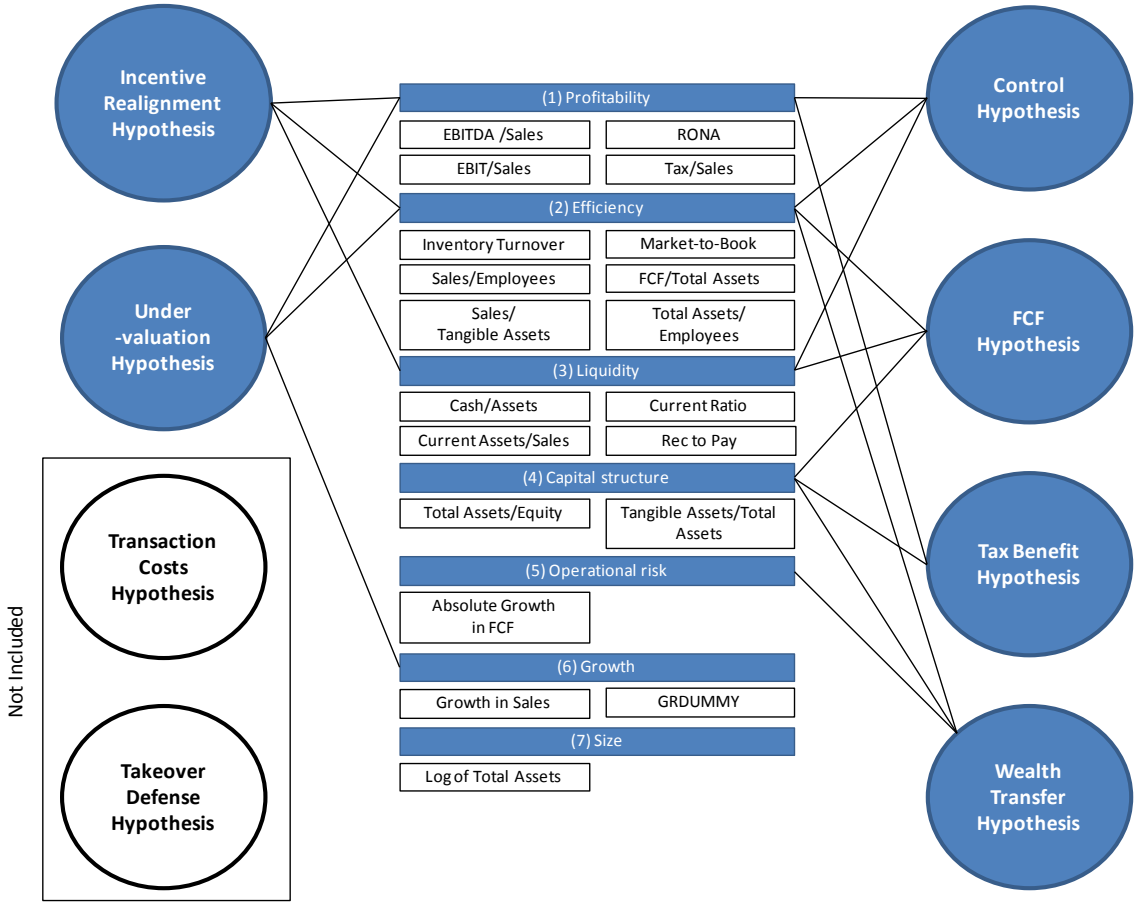
There are two ways to choose variables to include in the sample. One is where variables are chosen on an ad hoc basis, the other is to choose variables that originate from theory. The first approach has a lesser risk of missing an important variable, but might suffer from the model-fitting problem, i.e. that the model is statistically tailored to the sample (Palepu, 1986).

Variables chosen to be included in our statistical model are primarily derived from six of the eight general hypothesis in LBO theory and in turn represent seven quantifiable economic areas; (1) Profitability, (2) Efficiency, (3) Liquidity, (4) Capital structure, (5) Operational risk, (6) Growth, and (7) Size.

There are parameters not included in our selected areas that could still be of interest and most likely are subject to analysis by PE investors in a buy-out transaction, e.g. analysis of growth potential etc. We have not included such parameters due to measurement problems, and these financial ratios can not be assumed to be known by an outside investor, the above parameters are out of scope. Further, we do not elaborate on variables representing the Transaction Costs and Takeover Defense Hypothesis, since they are hard to quantify- Further, within the Takeover Defense Hypothesis previous studies have shown insignificant results. (Ambrose and Megginson, 1992)

For each economic area we have identified a set of ratios or absolute numbers, including the size parameter which is not covered in the economic theory explained earlier. The relationship between our seven defined areas and LBO theory are as follows (see next page):

Table 3: Variables derived from LBO theory



Profitability

The variables linked to the profitability area are derived from four of the eight theoretical frameworks. The Incentive Realignment Hypothesis is reflected in profitability since a company with low profitability and depressed margins could be considered to be a subject for change in the incentive program, thus being able to capitalize on more of its internal resources, where also increased ownership control plays a central role according to LBO theory. Given that there is room for improvement on operations not discounted in the share price that would support a buy

case for a PE investor, the Undervaluation Hypothesis plays a part. Taxes are a widely discussed topic in literature and are often pointed out as an important source of value creation in LBOs. In our set of variables we have included the profitability measure Tax to Sales, which indicate whether direct tax benefits can be earned for a PE investor in a target company that have high current tax costs.

Return on Operating Net Assets (RONA)

Typical ratios stating return on a capital base have been widely used in prior research. Powell (1997) used return on capital employed (ROCE), Palepu (1986), Ambrose and Megginson (1990) as well as Barnes (1990) used return on book value of equity (ROE) to proxy managerial efficiency. RONA is closely related to the efficiency area and ROE, but given our specific break up of economic areas, we have chosen to make adjustment and use the return from operating net assets, thus tuning the ratio to capture return on capital invested in the target's core operations and being a proxy for core profitability. We expect this ratio to have a negative Beta coefficient since PE investors seek to increase profitability of its target's operations and increase the level of control in the company.

EBITDA to Sales

The EBITDA margin has been infrequently used in earlier research, probably since most of these studies are made to distinguish all kind of acquisition targets from non targets. Nilsson and Såndberg (2002) did however find this ratio explanatory enough to be used in their final model. EBITDA has a close resemblance to operating cash flows and is a proxy of how large debt burden the target can bear. Banks calculate the amount of debt that can be extended based on, among other things, the EBITDA multiple (Nilsson and Såndberg, 2002). We expect the EBITDA margin to be of high interest for a PE investor seeking to increase leverage in the target company, thus we anticipate seeing a positive sign on the coefficient.

EBIT to Sales

The EBIT margin is closely related to the EBITDA margin and has been used by Stevens (1973), Kaplan (1989) and Andersson & Tallmark (2000). In essence the same logic to choose EBITDA can be applied to the EBIT margin as well. The main difference is the view on depreciation. The main purpose is to see if there is any difference in targets and non targets based on the amount of annual depreciation charged. A higher depreciation charge translates into a lower margin and indicates that the company has recently made larger investments and consequently fewer requirements for new investments in the short term future, leaving a larger expected margin for paying down new debt during a holding period. It might be of additional importance in the manufacturing industry where investments are capital intense. We expect this ratio to show a positive sign.

Tax to Sales

In LBO literature, tax benefits are widely discussed and are a popular explanation for value creation. Kosedag and Lane (2002) find that tax savings expressed as effective tax liabilities to equity is significant. Further, Lehn and Poulsen (1988), Marais, Schipper and Smith (1989), Kaplan (1989b), and Muscarella & Vetsuypens (1990) find tax savings to be relevant. At first we used effective tax rate as a proxy for potential tax savings, but since the data available was too poor and would result in a large cut of sample targets, we changed to tax in relation to sales. Since these two measurements are closely linked, we assume that the difference should be rather

insignificant and expect the relation to be positive, as large tax costs implies large value creation from tax savings in an LBO.

Efficiency

There is a fine line between efficiency and profitability. For example, a high asset turnover usually implies a high return on assets (see for example Johansson & Runsten, 2005). Variables we have chosen to label as efficiency ratios originate from the incentive, undervaluation and Control Hypothesis for the same reason as for profitability. Different from profitability, efficiency can be seen as a factor indicating if the company is able to produce steady cash flows. Additionally, looking at efficiency per employee or portion of asset, the efficiency area also incorporates the Wealth Transfer Hypothesis as inefficient use of internal resources may indicate that there are more optimal ways of employing the company's assets.

FCF to Total Assets

The Free Cash Flow (FCF) Hypothesis is primarily derived from Jensen (1986) and can be defined as the cash flows, generated by the company's operations, attributable to all holders of equity and debt. A high level of FCFs implies that there is room for additional debt as there are resources generated to cover additional interest expenses and amortizations. Lehn and Poulsen (1989) find that FCF in relation to Equity is significant in explaining LBOs. Powell (1997) finds similar results when using FCF to total assets. We have chosen to use FCF to total assets, because we expect the ratio to be more stable over time than when using equity as the denominator. FCFs are generated by the total asset pool, not only from the equity portion of the assets, consequently FCF to total assets makes sense when matching nominator and denominator accordingly to economic theory (Koller et al., 2005). Based on the Free Cash Flow Hypothesis we expect the correlation to be positive.

Inventory Turnover

Inventory turnover is calculated as cost of goods sold/ inventory, and we use it as a proxy for working capital management, i.e. core business efficiency. This ratio has not been widely used in earlier LBO literature, however Smith (1990) used inventory turnover when investigating if there is a difference in operational efficiency for targets and non targets post MBO transactions. We have no clear expectations on how this variable will behave. On one hand it is plausible that a high inventory turnover rate indicates that the company is able to produce steady free cash flows, on the other hand a low turnover rate could also indicate that there is room for improvement, thus being a case for the Undervaluation Hypothesis.

Market to Book

The market value of common equity in relation to the corresponding book value indicates how much of the expectations of a company's future value that is discounted into the current market price. The market to book has two motives for being included. Firstly companies with a, by an investor defined, low ratio can be considered undervalued and be an attractive buy. In order to fully assess this relation the market value should be set in relation to the book value of equity representing replacement cost of the company's assets (Palepu, 1986). Since this data is not accessible for replacement cost, we have chosen to use the common book value of equity as denominator. Secondly the ratio can also be treated as a proxy for management's performance, as efficient management would be able to convince the market about future earnings and consequently have more of the future value included in the current price (Powell, 1997). We consequently expect this ratio to have a negative coefficient.

Sales to Employees and Total Assets to Employees

In LBO transactions employee based ratios fulfill a purpose, as they indicate what potential value that can be achieved from transferring value between different stakeholders in line with the Wealth Transfer Hypothesis. Low sales or a low amount of assets per employee indicates possibilities for internal restructuring or layoffs. Alternatively, low sales per employee may indicate that the human capital in the company is used inefficiently and that e.g. the sales incentive program or IT system is inadequate. We expect both variables to have a negative coefficient.

Sales to Tangible Assets

The turnover of the company's tangible assets is an indicator of how much capital that is locked in the operations and is an indicator of how efficient management is in utilizing its invested capital. We have not seen this ratio being used frequently in LBO literature, however Nilsson and Såndberg (2002) uses this in their thesis. We have chosen to include this variable anyway, since it illustrates an important factor in the manufacturing industry, where we expect companies to have a large amount of tangibles. We anticipate that low sales to tangibles would imply rooms for improvement according to the Undervaluation Hypothesis thus show a negative sign.

All of the above ratios, except FCFs to total assets, drive our expectations in two different ways. A low efficiency ratio can be subject for improvement thus being negatively correlated. A high efficiency ratio could indicate that the company has characteristics of generating steady cash flows, making it a better target for additional debt financing, thus making the ratio positively correlated. We therefore do not have a strong opinion on which direction to expect the coefficient to have in any of the efficiency ratios above.

Liquidity

The amount of liquidity available in the company is a popular subject in LBO literature and the FCF Hypothesis states that excess cash is to be paid out in order to eliminate agency costs and induce increased bootstrapping in the company. Reducing the accessible fund in the company connects to the Incentive Realignment Hypothesis as managers get fewer resources to spend in projects generating inadequate returns and could provide an incentive to keep the company from breaking e.g. debt covenants. Reducing the liquidity margin relates to additional control being required from the company owners in order to protect their investment, as exit opportunities for their shares are more limited in the private market.

Cash to Assets

A large cash balance is beneficial for PE investors as it will decrease their initial investment. We have put the cash in relation to assets as we expect this ratio to be more stable over time. The ratio has been used directly or indirectly by most studies, e.g. by Belkaoui (1978), Palepu (1985), Barnes (1990), Powell (1997), Stowiliski, Zopounidis and Dimitras (1997), Ambrose and Megginson (1992) and Nadant and Perdreau (2004), to estimate liquidity and growth expansion resources. Low growth resources can imply that the company fails to generate enough funds to finance its expansion and that excess funds are an indicator of lack of growth opportunities. Looking at the manufacturing industry we expect that this ratio should have a positive coefficient, as a large cash balance in what is considered to be a fairly mature industry should imply excess cash possible to be paid out to the PE investor.

Current Assets to Sales

The turnover in liquid assets was used by Belkaoui (1978) and works as a proxy for the company's liquidity and is related to cash to assets. We have chosen to include this variable as well. Current assets can be described as the portion of total assets that can be converted into cash on a short term horizon, thus indicating how much liquidity that exists in the company besides excess cash. It can also be viewed as the portion of current assets from the core business operations that are required to generate the company's sales. In both instances, we expect this ratio to show a positive sign.

Current Ratio

Current ratio is calculated as current assets/current liabilities and a high current ratio indicates that there are excess short term funds available or that there is room for additional short term leverage. The current ratio has been used in earlier research by Dietrich and Sorensen (1984) as well by Barnes (1990) and we expect the ratio to demonstrate a positive correlation.

Accounts Receivable to Accounts Payable

Putting receivables in relation to payables indicate how much liquidity that arises from how the company handles suppliers and customers. A low ratio would indicate that the company is partly funded from managing its net working capital. This ratio has not been widely used in prior models and we have chosen to include it due to our model seek to predict LBOs in manufacturing and thus working capital management is expected to be of significance. Since a low ratio would indicate that there is high liquidity, a high ratio would suggest a room for operational improvements. Since we don't see one interpretation superior to the other in explaining the source of value creation, we are not able to predict if there will be a positive or a negative correlation.

Capital Structure

Capital structure, primarily leverage, relates to the FCF Hypothesis as increased leverage implies that the excess resources are tightening in order to eliminate agency costs. Capital structure incorporates the Tax Benefit Hypothesis as an increase in debt creates tax benefits from the tax deductions generated by new interest costs. New debt connects to the Wealth Transfer Hypothesis as new agreements are formed and new debt holders enter the company financing source.

Assets to Equity

Leverage has been used in most studies (e.g. Ambrose and Megginson (1992), Powell (1997), Barnes (1999) Bargeron et al. (2007)). Leverage illustrates how the company has handled debt and low leverage can signal how much excess capacity for new debt that the company has, thus being an attractive ratio to look at for PE investors. A high leverage indicates that there is less room for additional debt and/or that the company has tried to capitalize on potential growth opportunities unsuccessfully. We have used assets in relation to equity for statistical reasons as the ratio then gets the characteristics of starting at "0" (if negative equity) and then increases up until eternity as leverage increases to 100 percent (bankruptcy) and we expect that the leverage ratio has a negative coefficient.

Tangible Assets to Total Assets

A target's potential to pay its additional interest costs resulting from additional leverage is a key success factor in a post transaction. Tangible assets play a central role since they can be used as

collateral for new debt or be sold in case a company is close to break its debt covenants. This variable has been used before by e.g. Powell (1997) and we expect this ratio to have a positive relation.

Operational Risk

We have chosen to include a proxy for operating risk, which can be seen as a complement to capital structure. Low operating risk would imply that investors are more likely to take on additional financial risk and indirectly relates to the same hypothesis as capital structure and primarily to the Wealth Transfer Hypothesis, due to a potential increase in preferred risk level.

Absolute Growth in Free Cash Flows

Growth in free cash flows has not been widely used in prior research. Kaplan (1989a) uses changes in net cash flows from operations as a parameter when looking at post transaction development of target companies. We have incorporated a similar variable in our prediction model with some adjustments to the logic. Instead of using operating cash flows we have chosen to include the absolute value of growth in FCFs. The rationale behind this is that predictive stable cash flows are of interest for PE firms, seeking low operating risk. We predict this ratio to show a negative sign.

Growth

Betzer (2006) finds evidence that LBO targets have low growth opportunities, and an important part in valuation is the growth of a company. It is directly connected to the Undervaluation Hypothesis, which captures if the firm's assets can be employed in a better way than they are at the time of investment.

Growth in Sales

Growth in sales has been used in most studies e.g. Palepu (1986), Lehn and Poulsen (1989), Powell (1997), Ambrose and Megginson (1992), Kosedag and Lane (2002) and Nadant and Perdreau (2004) and is often combined with other measures for illustrating a growth-resource mismatch. On a standalone basis growth in itself ultimately does not indicate if the target is more or less likely to be acquired, even if it can be argued that high growth companies are likely targets for strategic buyers and low growth is more attractive to PE investors seeking mature companies. We have included two ratios of growth in sales, on a one year basis and on a two year average basis. Due to the inconclusiveness in only considering growth as a predicting variable we do not expect either a positive or negative relation from this ratio.

Growth Dummy

The purpose is to test whether PE firms invest in companies with (1) High growth opportunities, (2) No short term liquidity to finance its expansion and (3) Only having access to long term liquidity defined as leverage. The growth dummy has earlier been used by Palepu (1986) as a proxy for growth resource mismatch. Palepu (1986) additionally includes a resource mismatch combination of low growth, high liquidity and low leverage. We have chosen not to include the latter as this is tested by our other ratios used as proxies for leverage and liquidity individually. We believe that Palepu (1986)'s definition is contradictive in the sense that the value of "1" is assigned on targets with low leverage and stable businesses as well as for high growth companies with low short term liquidity. Accounting for only a growth mismatch defined by limited access to short term funds instead adds another dimension to the Undervaluation Hypothesis in our model, since we test if PE investors in LBO transactions find opportunities based on growth. We

have defined the growth dummy as being set to "1", if the company jointly has high sales growth, low liquidity and high leverage. High is defined as having a ratio above the industry average. We are inconclusive to what sign this dummy can be expected to show.

Size

The Log of Total Assets

The size parameter does not directly attach to any of the general hypotheses, but earlier studies has pointed out that size is an important factor in determining likelihood for acquisitions and that typical targets tend to be relatively small. Stevens (1973), Dietrich and Sorensen (1984), Palepu (1986) and Ambrose and Megginson (1992) all incorporate size in their study and find it to be of significance. Smaller companies require a lower investment costs, making the acquisition transaction easier to execute. We include the size factor and use Powell (1997) and Walter (1994)'s proxy of size as the log of total assets. We expect the variable to have a negative sign, even if Powell (2004), and Kim and Arbel (1998) find that it has a positive sign.

Time Inconsistency

A problem when using panel data[9] is time inconsistency. There are two time inconsistency problems: (1) Having data for several years and fitting the model to a multiyear period, the model ends up being suboptimal for each specific year. (2) If a company with data points in multiple years is only counted once, the true annual probability of takeover will be consistently over-/understated. This will in turn result in a survivorship bias in the calibration sample (Powell, 1997) *and* consequently in the holdout sample used for testing the model. That survivorship bias exists in the holdout sample have not, to our knowledge, been explicitly discussed in earlier research.

To help mitigate the first problem we chose to divide each year's observations with the industry average (after adjusting for outliers) of that year to achieve a more time consistent sample and ensure that the results are stable over time. This procedure increases the usefulness of the model's predictive ability (Barnes 1990). There are several ways to adjust accounting data to be more stable over time (Barnes, 1990). Barnes (1990) and Platt and Platt (1990) uses industry relative data. Powell (2004) tests a model with industry relative ratios (IRR) and a specific model that uses raw accounting data. He finds that the model with industry relative ratios has better prediction accuracy than the industry specific model. It is unclear though whether or not the industry specific model is better because it adjusts for differences between industries or if it mitigates the time inconsistency problem. Further, attitudes regarding buyouts might change over time, which would be hard to account for (Barnes, 1990). If a change in the economy was to incur in a period post the model calibration period, it could be argued that it might not be incorporated into the model. To some extent the model's Beta values would be affected, even if the beta values measures the relative relationship between the observations. Ultimately, how the model responds to changes in the economic environment depends on how the economic changes are captured in the independent variables (Barnes 1999).

The other time inconsistency problem is handled in two ways. (a) Testing the model on a holdout sample where each non-target is available for each year that it is listed. (b) Calculating the true average probability of takeover in our population. The first adjustment handles the survival bias,

[9] A data set containing observations on multiple phenomena observed over multiple time periods

which is included in earlier studies (see for example Palepu, 1986). Previous studies that use a holdout sample with multiyear observations fail to consider this issue, even though some (e.g. Powell, 2004) constructs the true takeover probability for each single year.

To create our holdout sample, we match the non-target distribution in the sample to the non-target population distribution on an annual basis.[10] We approximate that our population distribution is the true distribution of listed manufacturing companies. A total of 1,366 non-targets are included. The non-targets included in the hold-out sample are randomly generated, and hence a company can be included more than once and survivorship bias is mitigated.

Further we need to decide what to do if a company does not have data for t_{-1} for one or several of the ratios. Instead of removing these companies, we choose to take the data for t_{-2} or t_{-3}. We realize that this may distort the model, but argue that because we use IRR, the problem can be mitigated. The loss would otherwise be 134 data points, which we regard as being too many.

Model estimation

All variables except Market to Book are collected from company reports via Datastream, and several of them are similar in the way they are calculated. Each variable's contribution to the model and theory might therefore be small and there is a risk of multicollinearity (Barnes, 1999). To investigate the existence of multicollinearity and to calibrate the model to be as correct as possible, the following steps are used:

- Each variable is run in an univariate Logit regression to determine if it should be under consideration in the Logit model. If the variable is significant at a *p*-value of 0.25 it is included.
- The simple correlations between the included variables are further investigated. If the correlations are above 50 percent, one of the variables is excluded. If the correlation is between 20-50 percent the variable will be included in the initial model, but extensively tested for multicollinearity in the model optimization step.
- The model as a whole is investigated for multicollinearity.
- The initial model is estimated, and then the most insignificant variable is stepwise excluded until all variables are significant or the likelihood ratio test (testing if the nested[11] model .i.e. the model with one more variable, is better) shows that the previous model is better (see further Gujarati, 2003). The models are in addition tested with the Hosmer-Lemenshow test (see further Hosmer and Lemenshow, 2000).
- All variables excluded in earlier steps are retested for entry in the model with the likelihood ratio test.

(1) In the first step the variables Log of Total Assets, Cash to Assets, Receivables to Payables, Current Ratio, Current Assets to Sales, Tangible to Total Assets, Sales to Employees, Assets to Equity, Market to Book, Sales to Tangible Assets and Asset to Equity, were included (see table C in appendix).

(2) Next, the simple correlations of the different remaining variables are calculated. The variable Cash to Assets has a simple correlation with both Current Assets to Sales and Current Ratio of

[10] Our distribution collected from Datastream is used

[11] In computer programming, a nested function is a function which is encapsulated within another function

over 50 percent. The variable Tangible Assets to Total Assets has a simple correlation of above 50 percent with Sales to Tangible Assets. Therefore the variables Tangible Assets to Total Assets and Cash to Assets are excluded (See table E & F in appendix).

(3) The full model is investigated with the Variance Inflation Factor (VIF) and Tolerance (see further Gujarati, 2003). No variable has a high VIF factor or low Tolerance, indicating no multicollinearity problem.

(4) and (5) There is a methodological choice when eliminating variables to make the model as optimal as possible. The three ways are: (a) forward elimination, (b) backward elimination and (c) stepwise elimination. In forward elimination, the variables are tested in an univariate logic regression and ranked by their significance. They are added to the model in the same order, and after each step the model is tested if it has improved (Bursac et al, 2008), by for example using the likelihood ratio test. In backward elimination, all variables are added to the model and the model is reduced step by step until the model becomes less valid or all variables are regarded significant (given that there are no collinearities). Stepwise elimination is a mix, where you start with forward elimination and then do backward elimination and then forward again etc, which requires a lot of iterations (Bursac et. al, 2008). Other papers within takeover and bankruptcy studies mainly use backward elimination (e.g. Skogsvik 1988), but we have chosen to use stepwise elimination. (2) The significance value of 0.1 is chosen as the significance hurdle. The choice of significance value can be discussed, but 10 percent is regarded as small (Newbold et. al, 2003). Our sample still includes missing values in some of the categories and the likelihood ratio test (LR test) requires the number of observations to be the same amount. The model is therefore estimated with the same number of observations as the previous model in each step. If a variable has a low beta coefficient, even if it is significant, a LR test to exclude that variable will be carried out.

The Hosmer-Lemenshow test measures the goodness of fit of a logistic model, and groups the predictions of the logistic model into ten sub-groups (Hosmer and Lemenshow, 2000). It is a better measure of fit than the ordinary McFadden when the covariance matrixes are the same as the number of observations. If the Hosmer-Lemenshow goodness of fit test statistic is not significant, we fail to reject the null hypothesis (that there is no difference between observed and model-predicted values). Well-fitting models are not significant in the Hosmer-Lemenshow test (Hosmer and Lemenshow, 2000).

Cut-off points

We need to choose a probability cut-off point to determine when a company is to be classified as a target. As Palepu (1986) points out, many earlier studies arbitrarily use 50 percent as cut-off point . If the sample sizes are equal and the purpose of the study is to classify as many companies as correct as possibly, this might be reasonable. However if the purpose of the study is to be able to distinguish targets and build a trading strategy, the cost of the errors have to be estimated. The cost of a type 1 and type 2 error is not equal (Powell, 2004). It is reasonable to assume that a trader would regard a type II error more costly. For example, if a firm is placed in an equally weighted portfolio, and the firm is a target the portfolio earns an abnormal return of *r*, if the next firm that is placed in the portfolio is a non target (type II error), the portfolio would earn *r/2* instead (Powell, 2004). The object then is to minimize the total cost. Theodossiou (1996) derives the following classification rule:

$$MinE(C) = W_T Type\ I + W_{NT} TYPE\ II$$

The different weights (W) are the investor's specific weight attached to the type of error. Clearly, as both Powell (2004) and Theodossiou (1996) also recognizes, the cost of committing a Type I error is greater than committing a Type II error. Powell (2004) however in contrast to Theodossiou (1996) recognizes that setting $W_T = W_{NT}$, would result in a too low cut-off value, even if you do not know the specific weights. If the objective of the model is to earn abnormal returns then, as Powell (2004) further states, setting $W_T = W_{NT}$ would imply minimizing the total errors and not optimizing returns. To optimize returns, portfolios are created for each cut-off deciles, the optimal portfolio selection would be where the proportion of targets is maximized (Powell, 2004). We choose to follow Powell and divide our sample into ten deciles (see table D in appendix) and choose the cut-off value to be the value where the proportion of targets is maximized.

Empirical Results and Analysis

Summary of Findings

The final model includes Log of Total Assets, Receivables to Payables, Cash to Assets and Assets to Employees (see table 7). Cash to Assets and Log of Total Assets have signs that are not expected theoretically. Asset to Employees is still not significant at the 10 percent. The Hosmer-Lemenshow indicates a good model fit.

Our results reject the FCF Hypothesis, but find support for the Control Hypothesis by a positive sign for Receivables to Payables and a negative sign on Cash to Assets, indicating that PE firms look for firms which they can improve due to their higher quality of ownership. This would also fit with the negative sign on Asset to Employees, even though that variable is not significant. The reasons for why Cash to Asset gives a negative coefficient is unclear, however a theory could be that PE firms invest in companies with future growth opportunities that are short term capital constraint. The fact that the growth variable is not significant does not necessarily contradict this as we measure past growth with that variable. The positive, though not significant, Asset to Equity coefficient in the initial model supports this. Our pseudo R^2 is 33.77 percent is quite good compared to for example Palepu (1986) that only reports a R^2 of maximum 12.45 percent, hence our model is better to explain the variation in a firm's acquisition probability. This is expected as our data is more only on PE-firms and only on one industry, making our model more specific. We reach a 70.69 percent correct classification rate in the estimation sample with a cutoff value of 0.8941 (see table 10). The model does even better on the holdout sample and predicts 97.50 percent of the non-targets and targets correctly. However the model is worse in predicting targets than non-targets and the positive predictive ability is 57.69 percent, which is still better than in earlier studies e.g. Powell, (2004), that achieves a positive predictive ability of 4.76 percent in his estimation sample with his best model.

Descriptive Data and Model Construction

Table 4: Descriptive variable data by sample group

	Targets					Non targets					Mean		Exp.
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev	Min	Max	difference	T-test	sign
Market to book	84	0.78	0.96	-1.61	4.94	86	1.11	1.05	-0.51	5.13	-0.32	0.038	-
Rec to Payables	88	1.64	1.17	0.00	3.74	88	0.60	0.54	0.11	3.42	1.04	0.000	?
Inventory Turnover	80	1.06	0.68	0.19	3.13	87	1.00	0.82	0.08	3.65	0.06	0.619	?
Sales to Employees	79	1.33	1.03	0.19	3.65	87	0.97	0.81	0.08	3.62	0.35	0.016	-
Asset to Employees	87	0.81	0.70	0.10	3.72	88	1.08	0.80	0.09	3.83	-0.27	0.018	-
EBITDA Margin	87	-0.38	1.45	-2.65	4.94	88	-0.38	2.29	-5.62	12.65	0.00	0.994	+
Abs value of growth in FCF	87	0.86	1.12	0.00	4.27	88	0.99	1.19	0.00	4.32	-0.13	0.457	-
Tax to Sales	87	0.45	3.18	-12.58	8.45	83	0.80	3.13	-12.58	11.88	-0.34	0.480	+
Sales to Tangible Assets	88	0.76	0.77	-2.53	3.99	88	0.97	0.93	0.05	4.12	-0.21	0.098	-
Cash to Assets	87	0.41	0.65	0.00	3.85	88	0.98	0.87	0.00	3.03	-0.56	0.000	+
Log Total Assets	88	1.20	0.16	0.79	1.71	88	1.08	0.16	0.75	1.55	0.12	0.000	-
Current Assets to Sales	88	0.59	0.51	0.13	3.55	88	0.90	0.68	0.15	3.36	-0.31	0.001	+
Tangible to Total Assets	88	1.18	0.69	-0.20	3.58	88	0.91	0.64	0.10	2.83	0.27	0.008	+
EBIT Margin	87	0.04	1.03	-1.60	4.40	88	0.06	1.46	-2.72	7.68	-0.01	0.950	+
Free Cash Flow to Assets	88	-0.72	1.92	-6.06	10.31	88	-0.50	2.16	-7.83	11.22	-0.22	0.468	+
Asset to Equity	88	1.39	1.38	-1.47	3.52	88	1.19	0.74	-1.37	3.51	0.20	0.232	-
Growth in Sales	88	30.94	822.84	-5659.58	3067.68	88	-34.18	1068.26	-5026.83	3744.44	65.12	0.651	?
RONA	85	-0.97	13.94	-67.97	24.21	88	-0.24	9.90	-67.97	30.40	-0.73	0.692	-
Current Ratio	81	0.57	0.55	0.08	4.31	88	1.15	1.18	-2.92	4.46	-0.58	0.000	+
2 Years growth in Sales	88	22.16	713.52	-4689.42	1799.74	88	-70.72	943.43	-5571.28	1997.80	92.88	0.462	?
GRDUMMY	88	0.43	0.50	0.00	1.00	88	0.38	0.49	0.00	1.00	0.06		?

All variables except Two Year Growth in Sales and the Growth Dummy have by construction population means of 1. The largest differences between targets and non targets are in the variables Receivables to Payables, and the One and Two Year Growth Rates. Testing first for equal variance, and then carrying out the corresponding t-test shows that at a 10 percent two tailed test the means for Market-to-Book, Receivables to Payables, Sales to Employees, Asset to Employees, Sales to Tangible Assets, Cash to Assets, Log Total Assets, Current Assets to Sales, Tangible to Total Assets, and Current Ratio are not equal. The most surprising fact with this test is that none of the profitability ratios EBIT margin, EBITDA margin or RONA have a significant p-value. Variables with a sign not corresponding to the expected sign are Sales to Employees, EBITDA Margin, Tax to Sales, Cash to Assets, Log of Total Assets, Current Assets to Sales, EBIT margin, Free Cash Flow to Assets, Asset to Equity and Current Ratio. It is unexpected that Cash to Assets, Current Assets to Sales, and Current ratio, which in some form might be characterized as short term liquidity, shows a negative sign compared to the positive expected sign. This might indicate that PE investors actually buy companies with lack of resources. The positive sign on Asset to Equity, support this notion too.

Next we run a univariate Logit regression with each one of the variables individually:

Table 5: Univariate regression results

Variable	Beta Coef.	Std Err,	P>|z|
Log Total Assets	5.115	1.129	0.000
Cash to Assets	-1.028	0.242	0.000
Rec to Payables	1.425	0.267	0.000
Current Ratio	-0.859	0.254	0.001
Current Assets to Sales	-1.005	0.330	0.002
Tangible to Total Assets	0.626	0.240	0.009
Sales to Employees	0.424	0.179	0.018
Asset to Employees	-0.499	0.218	0.022
Market to book	-0.341	0.170	0.045
Sales to Tangible Assets	-0.307	0.189	0.105
Asset to Equity	0.166	0.139	0.231
GRDUMMY	0.236	0.308	0.443
Abs value of growth in FCF	-0.099	0.133	0.455
2 Years growth in Sales	0.000	0.000	0.464
Free Cash Flow to Assets	-0.055	0.076	0.468
Tax to Sales	-0.035	0.050	0.479
Inventory Turnover	0.102	0.206	0.620
Growth in Sales	0.000	0.000	0.650
RONA	-0.005	0.013	0.689
EBIT Margin	-0.008	0.120	0.949
EBITDA Margin	-0.001	0.079	0.994

In the univariate regression we get some of the same indications as by doing the t-test above. Total Assets was significant above as well as Receivables to Payables, Cash to Assets, Current Ratio and Current Assets to Sales. Sales to Employees and Asset to Employees are also significant both with the t-test and the univariate regression. What is more interesting is that Tax to Sales is not significant, and will be excluded. This is inconsistent with earlier research in Europe (Nadant and Perdreau, 2004) and North America (see for example Belkoui 1978 and Kaplan 1989). The studies in North America are however not only on PE buyouts, so our results might indicate that the Tax Benefit Hypothesis is only significant when all buyouts are considered. This would either implicate that a) strategic buyers are more interested in tax benefits or b) targets within other industries than the manufacturing industries are more interesting when it comes to tax benefits. Worth pointing out is that industry relative ratios are not used in these studies and the sample period differs, which could partly explain the difference. Further worth noting is that the profitability measures are still insignificant. This is in contrast with Powell (1997) that finds that ROCE is significant at the late sub period of 1988-1991, but not for his full period. Generally, prior performance in this area does not seem to affect takeover likelihood in our study nor in previous studies.

Initial model

We now construct our initial model based on the univariate and correlation results:

Table 6: Initial model results

Number of obs	157			
LRchi2(9)	82.36			
Prob>chi2	0			
Log Likelihood	-66.925459			
Psuedo R2	0.3809			
Hosmer -Lemeshow test	0.1528			
Variable	**Coefficent**	**Std Err.**	**z**	**P>|z|**
Log Total Assets	6.14742	1.69707	3.62	0.000
Rec to Payables	1.30942	0.32079	4.08	0.000
Current Ratio	-0.32736	0.32714	-1.00	0.317
Current Assets to Sales	-1.03578	0.55914	-1.85	0.064
Tangible to Total Assets	-0.00758	0.35434	-0.02	0.983
Sales to Employees	0.01802	0.28880	0.06	0.950
Asset to Employees	-0.68864	0.41761	-1.65	0.099
Market to book	-0.48527	0.28171	-1.72	0.085
Asset to Equity	0.06606	0.22152	0.30	0.766
Constant	-6.42532	2.00177	-3.21	0.001

In the initial model the significant variables are Log of Total Assets, Receivables to Payables, Asset to Employees and the constant on the 5 percent level. The Hosmer-Lemenshow test (HL-test) is not significant and we therefore reject the null hypothesis of bad model fit. The least significant variables are now excluded stepwise to get the intermediate model. 77.71 percent of the companies are correctly classified in the initial model on a *50 percent cut-off point.*

Final Model

Log of Total Assets is the variable with the highest beta coefficient, and our model hence predicts that size is an important factor. The Beta coefficient does not show the expected sign, however Kieschnick (1998) find size to be positively correlated in study. Nilsson and Såndberg (2002), further concludes that PE firms according to their interviews try to buy the largest companies within each business segment. Cash to Assets has a sign that is not expected theoretically, we choose to leave it in the model. Asset to Employees is still not significant at the 10 percent level but is still left in the model as the HL test otherwise indicate a bad model fit (8.65 significance). The first Prob>Chi2 that is reported is the Mcfadden ratio which is an uncertain indicator when the number of covariance groups are the same as the number of observations (Hosmer-Lemenshow, 2000). Therefore the HL test is used. The result indicates a good model fit. Below the results, with the arbitrary cutoff point 50 percent, is reported.

Table 7: Final model results

Number of obs	174			
LRchi2(11)	81.450			
Prob>chi2	0.000			
Log Likelihood	-79.869			
Psuedo R2	0.3377			
Hosmer -Lemeshow Prob > chi2	0.2659			
Variable	**Coefficent**	**Std Err.**	**z**	**P>|z|**
Log Total Assets	5.2423	1.4118	3.71	0.0000
Rec to Payables	1.2171	0.2692	4.52	0.0000
Cash to Assets	-0.8209	0.3146	-2.61	0.0090
Asset to Employees	-0.5042	0.3235	-1.56	0.1190
Constant	-6.1605	1.5658	-3.93	0.0000

Table 8: Classification table for estimation sample using cut off value 0.5

Classified + if Predicted Pr(D)>=0.5			
	TRUE		
Classified	D	~D	Total
+	65	14	79
-	21	74	95
Total	86	88	174
Sensitivity Pr(+|D)	75.58%		
Specificity Pr(-|~D)	84.09%		
Positive predictive value Pr(D|+)	82.28%		
Negative predictive value Pr(~D|-)	77.89%		
FALSE + rate for TRUE ~D Pr(+|~D)	15.91%		
FALSE - rate for TRUE D Pr(-|D)	24.42%		
FALSE + rate for classified + Pr(~D|+)	17.72%		
FALSE - rate for classified - Pr(D|-)	22.11%		
Correctly classified	79.89%		

All our variables include assets, and another explanation could be that in the manufacturing industry, the combination of assets is easier to value than in industries with more intangible assets. The focus then by PE firms would be on the indicators most easily valued. Receivables to Payables is a new variable in takeover likelihood studies and it is the variable with the second highest coefficient. Together with the fact that the Cash to Asset coefficient is negative, we reject the FCF Hypothesis. However, the Receivables to Payables positive coefficient might fit with the Control Hypothesis indicating that PE firms look for firms which they can improve due to their higher quality of ownership. This would also fit with the negative sign on Asset to Employees, even though that variable is not significant.

Our pre-adjustment predictive ability of 79.89 percent is in line with earlier studies and can be regarded as quite satisfactory. The cut-off value is as stated in the methodology section not optimal, and therefore the targets are grouped into deciles.

Table 9: Deciles matrix

Cut-off value	Total	Targets	Non-targets	% Targets	% Non-target
0.2766	118	77	41	65%	35%
0.4697	85	69	16	81%	19%
0.5672	70	60	10	86%	14%
0.6762	56	52	4	93%	7%
0.7892	45	43	2	96%	4%
0.8941	35	35	0	100%	0%
0.9075	26	26	0	100%	0%
0.9492	18	18	0	100%	0%
0.9798	9	9	0	100%	0%
0.9969	1	1	0	100%	0%

As we can see the optimal cut-off value is at 0.8941, which gives the following predictive value in the estimation sample:

Table 10: Classification table for estimation sample using cut off value 0.8941

Classified + if Predicted Pr(D)>=0.8941			
	TRUE		
Classified	D	~D	Total
+	35	0	35
-	51	88	139
Total	86	88	174
Sensitivity Pr(+|D)	40.70%		
Specificity Pr(-|~D)	100.00%		
Positive predictive value Pr(D|+)	100.00%		
Negative predictive value Pr(~D|-)	63.31%		
FALSE + rate for TRUE ~D Pr(+|~D)	0.00%		
FALSE - rate for TRUE D Pr(-|D)	59.30%		
FALSE + rate for classified + Pr(~D|+)	0.00%		
FALSE - rate for classified - Pr(D|-)	36.69%		
Correctly classified	70.69%		

The model correctly classifies 70.69 percent of the companies, which is still is good compared to other studies, however this figure is overstated due to the fact that we used a choice-based sample.

Palepu, however (1986) shows that the probabilities estimated are overstated if a state-based sample (not a representative sampling from the true population) is used. Palepu (1986) states that the bias does not alter the rankings of the companies, and shows that the true probability can be calculated using Bayes' formula. To see how the true probability changes and to put our cut-off value of 89.41 percent probability of being a target into context, we show what the true unbiased probability of this cut-off point would be on our state-based sample:

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

where, p^* = Biased estimate

p = True estimate

n_1 = # of targets in the sample

n_2 = # of non-targets in the sample

N_1 = # of targets in the population

N_2 = # of non-targets in the population

Restating the formula in terms of p:

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

Here we have to decide what the population is. Because the model estimates if a company is a target given last year's data, the number of targets and non-targets must be that year's number of targets and non-targets. An average over our time-period is 1.86 percent targets per year. This would for example indicate that our cut-off value of 89.41 percent chance of being a target would be a real probability of being a target of:

$$p = 0.8941 * \frac{0.0186 * \left(1 - \frac{86}{174}\right)}{\frac{86}{174} * (1 - 0.0186) + 0.8941 * \left(0.0186 - \frac{86}{174}\right)} = 14.07\ percent$$

Important to note is that this calculation does not change the rank of the companies, and we can use are model as is when testing its predictive ability (Palepu, 1986). This means that all companies classified as targets in our estimation sample have at least a 14.07 percent probability of being a target.

Model evaluation

Table 11: Classification table for holdout sample using cut off value 0.8941

Holdout sample Classified + if Predicted Pr(D)>=0.8941	TRUE		
	D	~D	Total
+	15	11	26
-	23	1313	1336
	38	1324	1362
Sensitivity Pr(+|D)	39.47%		
Specificity Pr(-|~D)	99.17%		
Positive predictive value Pr(D|+)	57.69%		
Negative predictive value Pr(~D|-)	98.28%		
FALSE + rate for TRUE ~D Pr(+|~D)	0.83%		
FALSE - rate for TRUE D Pr(-|D)	60.53%		
FALSE + rate for classified + Pr(~D|+)	42.31%		
FALSE - rate for classified - Pr(D|-)	1.72%		
Correctly classified	97.50%		

Our model does not only do well in terms of correctly classifying companies as a whole in the holdout sample, it additionally gets a positive predictive value of 57.69 percent which compared to earlier studies that uses our cut-off rule is good (e.g. Powell (2004) achieves a positive predictive ability of 4.76 percent in his estimation sample with his best model).

One of the reasons might be how we have handled the survivability problem, i.e. non-targets might be in the model several times, but with different data. This might affect the number of type II errors, as a company that was predicted for example in 2002 to be a non-target, might not have changed its accounting data a lot in 2004. We argue however that our way of dealing with this is more reasonable, as an investor would look each year at all companies and run this or a similar model. If we would remove all non-targets that appear more than once in the holdout sample, (and leave only one observation), the number of non-targets in the holdout sample would be 915. It would affect our positive predictive value in a positive way, and our negative predictive value in a negative way. As our goal is to maximize the positive predictive value, not accounting for the bias would be even better.

When testing for LBOs in our hold-out sample, some companies do not have the required data. Out of a total of 1,411 companies (of which 46 are targets), 8 targets and 38 non-targets can not be classified. This is unfortunate, but gives the weight 38 targets to 1,324 non-targets in the population, i.e. 2.87 percent. This is a bit higher than the true average probabilities of 1.86 percent above, which should according to Palepu (1986) be used in prediction modeling. This

error can be mitigated by adjusting for the bias in the prediction sample. Palepu (1986) shows that the error *e* can be calculated as follows:

$$e = \frac{m_1\left(\frac{N_1}{n_1}\right) + m_2\left(\frac{N_2}{n_2}\right)}{n_1 + n_2} * \frac{n_1 + n_2}{N_1 + N_2}$$

where, m_1 = # of Type 1 errors

m_2 = # of Type 2 errors

n_1 = # of targets in the sample (holdout)

n_2 = # of non-targets in the sample (holdout)

N_1 = # of targets in the population

N_2 = # of non-targets in the population

As we have stated above the average percentage of targets in the population is 1.86 percent, we therefore get:

m_1 = 23

m_2 = 11

n_1 = 38

n_2 = 1324

N_1 = 0.0186*N_2/(1-0.0186)

N_2 = N_2

$$e = \frac{23\left(\frac{0.0186N_2/(1-0.0186)}{38}\right) + 11\left(\frac{N_2}{1324}\right)}{38+1324} * \frac{38+1324}{\frac{0.0186N_2}{(1-0.0186)} + N_2} = 1.94 \text{ percent}$$

Because of our holdout sample, we actually would in expectation have a *lower* error rate in the true population.

To see if our model suffers from heteroscedasticity we run our model with the Huber-White-sandwich test, which groups the data into clusters in order to account for outliers. Our results are shown below. As you can see, Asset to Employees becomes less significant, and the standard error changes with 33 percent for Asset to Employees and 19 percent for Log of Total Assets. Hence, we can not rule out heteroscedasticity in Asset to Employees, but conclude that heteroscedasticity is not that important in the other variables and that the model is still significant. (See further Wooldridge, 2002)

Table 12: Final model with Huber-White-sandwich test

Number of obs	174			
Wald chi2(4)	41.630			
Prob>chi2	0.000			
pseudolikelihood	-79.869			
Psuedo R2	0.3377			
Hosmer -Lemeshow test 0.3	0.2659			
Variable	**Coefficent**	**Std Err.**	**z**	**P>|z|**
Log Total Assets	5.24228	1.6754	3.13	0.002
Cash to Assets	-0.82093	0.3514	-2.34	0.019
Rec to Payables	1.21709	0.2563	4.75	0.000
Asset to Employees	-0.50416	0.4310	-1.17	0.242
Constant	-6.16053	1.8185	-3.39	0.001

Summary & Conclusion

Research in takeover prediction has generally applied a framework that fails to account for the relationship between target and acquirer. Powell (1997) finds that taking into account the difference between hostile and friendly takeovers in takeover prediction modeling increases predictive performance. Kim and Arbel (1998) achieve in their study of the hospitality industry a positive prediction value of 57.9 percent. However, Kim and Arbel (1998), use naïve state-based holdout sample with equal number of targets and non-targets, which overstates their positive prediction value. This paper addresses this issue by limiting the model to only include PE buyouts within the manufacturing industry, and uses a more representative hold-out sample that takes time inconsistency into account. The results confirms that taking into account the difference between takeovers do improve the predictive ability. Furthermore, compared to for example Palepu (1986) that achieves 12.45 percent R^2, the model has a high explanatory power (33.77 percent).

Further investigation into the characteristics of takeover targets within the manufacturing industry shows that size and Receivables to Payables (a variable not used in earlier studies) are important determinants.

Our model manages to predict 97.5 percent of all companies in the holdout sample correctly and is better at predicting targets and non-targets than prior research, with the exception of Barnes (2000) who achieves a 97.7 percent correct classification rate. However, since a takeover prediction models primary usage would be to try to earn abnormal returns, the positive predictive ability of the model is the key factor. A positive predictive ability of 57.69 percent is considerably better when compared to other prominent research. Barnes (2000) in comparison is not able to predict one single target with his models. Powell (2004) shows that it is possible to earn abnormal returns using a takeover prediction model, and if this still holds, a model with our level of predictive ability would soon break the bank. We believe the following are the main explanations for our results being different in comparison to earlier studies:

(1) Total correct classification rate and positive predictive ability seems to improve if only one specific transaction type is used as a test group. This is supported in Powell's (1997) findings that there is a difference between hostile and friendly bids.
(2) Predictive ability improves further when using a specific industry to calibrate the model, similarly to what Kim and Arbel (1998) find in the hospitality industry.
(3) The model's predictive ability improves when accounting for survivorship bias in both the estimation sample and the hold-out sample.
(4) As Powell (2004) also finds, the use of industry relative ratios, improves the model by increasing the stability of ratios *within* the estimation sample over time.

Economic Theory

The variables that are included in the final model are: (1) Receivables to Payables, (2) Log of Total Assets, (3) Assets to Employees, and (4) Cash to Assets. All except Asset to Employees are significant at the 1 percent level. Asset to Employees are significant at 11.9 percent level. Log of Total Assets and Cash to Assets show an opposite sign to what was expected.

An explanation for the size factor could be that PE firms try to buy the market leader within each industry. This is further supported by the results in Nilsson and Såndberg (2002), and Kim and Arbel (1998).

The variable with the second largest Beta coefficient is Receivables to Payables, and the positive sign on this ratio, in combination with the negative sign on Asset to Employees, suggests that PE firms prefer inefficient targets whose operating activities can be rationalized during the holding period. Consequently the results are in favor of the Control Hypothesis, the Wealth Transfer Hypothesis or the Undervaluation Hypothesis. It is possible that all of the above hypotheses are valid. However, as all three ratios, Receivables to Payables, Asset to Employees, and Cash to Assets indicate inefficiency, we believe that there is most support for the Control Hypothesis.

In conclusion: Large and financially inefficient companies with excess employees experience the highest likelihood of being an LBO target in the U.S. Manufacturing Industry 1997-2006.

Further Research

We have identified three areas of interest to investigate further given our results:

1. Test if it is possible to obtain similarly good results within other industries.
2. Test our model's robustness over time.
3. Test our model's ability to earn abnormal returns in the period following the credit crunch of 2008.

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Appendix

For table A, and B transactions include all PE deals in the CapitalIQ database between 1985/01/01 and 2007/06/30. Transaction value is Enterprise value defined as the sum of net debt and equity used to finance the transaction using dollar currency of 2007. For the transactions where enterprise value was not recorded, values have been computed by Strömberg (2008).

Table A: UK LBO activity expressed in Enterprise value

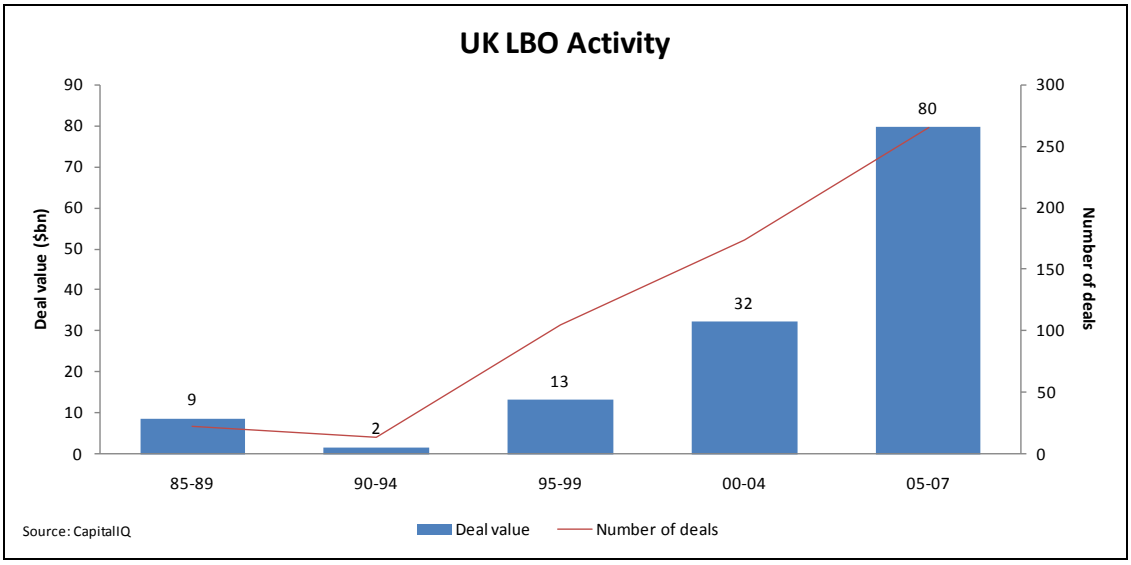

Table B: Europe (excl. UK) LBO activity expressed in Enterprise value

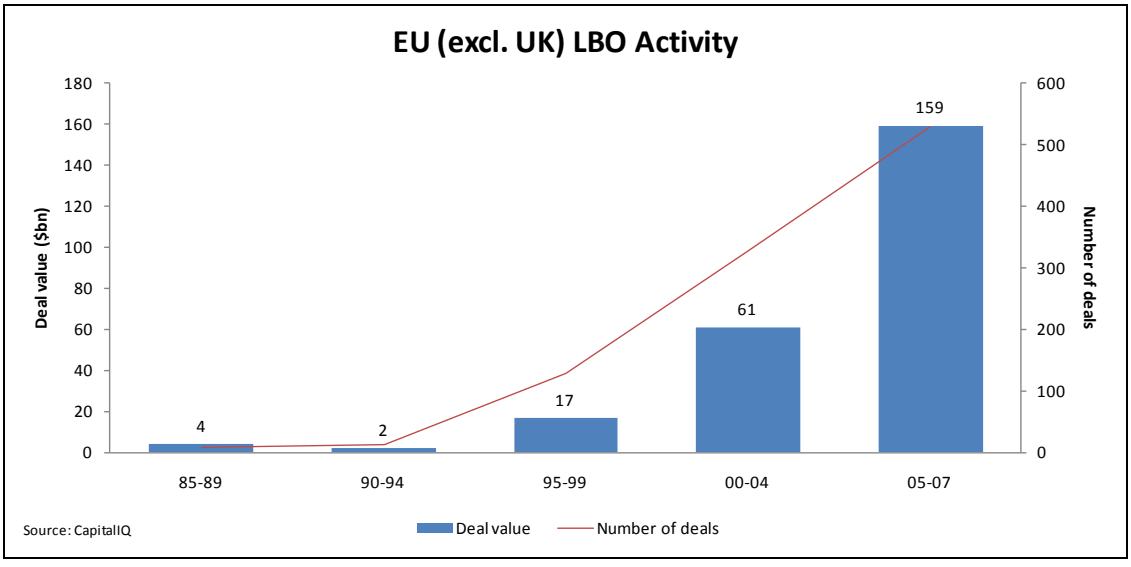

Table C: Definitions of financial ratios

1. *Market to book* = Share price$_{t=0}$ / Book value of Equity$_{t=0}$
2. *Receivables to Payables* = Account receivables $_{t=0}$ / Account payables $_{t=0}$
3. *Inventory Turnover* = Cost of Goods Sold$_{t=0}$ / Inventory$_{t=-1}$
4. *Sales to Employees* = Sales$_{t=0}$ / Employees$_{t=0}$
5. *Total Assets to Employees* = Total Assets$_{t=0}$ / Employees$_{t=0}$
6. *EBITDA Margin* = EBITDA $_{t=0}$ / Sales $_{t=0}$
7. *Absolute Value of Growth in FCF* = ABS((FCF $_{t=0}$ - FCF $_{t=-1}$)/FCF $_{t=0}$)
8. *Tax to Sales* = Tax on net profit $_{t=0}$ / Sales $_{t=0}$
9. *Sales to Tangible Assets* = Sales $_{t=0}$ / Tangible Assets $_{t=-1}$
10. *Cash to Assets* = Cash $_{t=0}$ / Total Assets $_{t=0}$
11. *Log of Total Assets* = Ln (Total Assets$_{t=0}$)
12. *Current Assets to Sales* = Current Assets$_{t=-1}$ / Sales$_{t=0}$
13. *Tangible Assets to Total Assets* = Tangible Assets$_{t=0}$ / Total Assets$_{t=0}$
14. *EBIT Margin* = EBIT$_{t=0}$ / Sales$_{t=0}$
15. *FCF to Assets* = Free Cash Flow$_{t=0}$ / Assets$_{t=-1}$
16. *Total Assets to Equity* = Total Assets$_{t=0}$ / Book value of equity$_{t=0}$
17. *Growth in Sales* = (Sales$_{t=0}$ - Sales$_{t=-1}$)/Sales$_{t=0}$
18. R_{ONA} = EBIT$_{t=0}$*(1-T$_c$) / (Net debt$_{t=-1}$ + Book value of Equity$_{t=-1}$)
19. *Current Ratio* = Current Assets$_{t=0}$ / Current Liabilities$_{t=0}$
20. *2 Years growth in Sales* = [(Sales$_{t=0}$ - Sales$_{t=-1}$)/Sales$_{t=0}$ + (Sales$_{t=-1}$ - Sales$_{t=-2}$)/Sales$_{t=0}$] / 2

Table D: Total number of observations winsorized back per variable

Variable	Number
MTBV	2,272
Asset Equity	2,275
EBIT to Sales	2,253
Ebitda to sales	2,169
RONA	1,867
Rec to Pay	1,657
ABS growth in FCF	1,497
FCF to total assets	1,448
Current Assets IB to Sales	1,237
Growth in Sales	989
Sales to Tangible Assets IB	928
Current ratio	915
Sales to Employees	862
Inventory Turnover	707
Total assets to employees	612
Tax to Sales	607
LN Total Assets	16
Tangible to Total Assets	14
2yr av sales growth	0
Cash to Assets	0

Table F: First step model run results

Number of obs	157			
LRchi2(11)	86.61			
Prob>chi2	0			
Log Likelihood	-64.004008			
Psuedo R2	0.4036			
Hosmer -Lemeshow test	0.312			
Variable	**Coefficent**	**Std Err.**	**z**	**P>|z|**
Log Total Assets	7.25295	1.95373	3.71	0.000
Cash to Assets	-0.86661	0.51672	-1.68	0.094
Rec to Payables	1.26918	0.32297	3.93	0.000
Current Ratio	-0.08139	0.42592	-0.19	0.848
Current Assets to Sales	-0.25963	0.65726	-0.40	0.693
Tangible to Total Assets	0.16547	0.53151	0.31	0.756
Sales to Employees	0.14196	0.29745	0.48	0.633
Asset to Employees	-0.87606	0.45655	-1.92	0.055
Market to book	-0.32357	0.27611	-1.17	0.241
Sales to Tangible Assets	0.52289	0.52556	0.99	0.320
Asset to Equity	-0.00120	0.22547	-0.01	0.996
Constant	-8.52785	2.79773	-3.05	0.002

Table E: Variable correlation matrix

	MTBV	Rec to Pay	Inv. Turn.	Sales to Empl	Ass to Empl.	Ebitda Margin	ABS growth	Tax to Sales	Sales to Tangible	Cash to Assets	LN Tot Ass	Curr Ass to Sales	Tang. to Tot Ass	Ebit Margin	FCF/ Tot Ass	A/E	Sales Growth	RONA	Current ratio	2 y Sales Growth
Market-to-Book																				
Rec to Pay	-0.09																			
Inventory Turnover	0.02	0.07																		
Sales to Employees	0.02	0.10	0.97																	
Total assets to employees	0.12	0.03	0.05	0.05																
Ebitda to sales	-0.01	0.21	-0.06	-0.06	0.02															
ABS growth in FCF	-0.02	-0.02	-0.01	-0.01	0.00	0.01														
Tax to Sales	0.12	-0.11	0.01	0.01	0.12	-0.14	-0.06													
Sales to Tangible Assets	0.03	-0.08	0.10	0.09	-0.01	-0.06	0.11	0.03												
Cash to Assets	0.22	-0.03	-0.04	-0.04	0.41	0.09	0.00	0.13	0.11											
LN Total Assets	0.09	-0.10	0.15	0.16	0.31	-0.21	-0.09	0.12	-0.24	-0.07										
Current Assets IB to Sales	0.10	0.06	-0.32	-0.31	0.37	0.28	0.00	-0.03	-0.19	0.56	-0.10									
Tangible to Total Assets	-0.08	0.13	0.22	0.22	-0.08	-0.03	-0.09	-0.03	-0.54	-0.37	0.12	-0.21								
EBIT to Sales	0.01	0.17	-0.04	-0.04	0.02	-0.14	0.01	-0.17	-0.06	0.11	-0.17	0.26	0.00							
FCF to total assets IB	-0.03	0.14	-0.02	-0.02	0.02	0.48	0.01	-0.08	0.00	0.10	-0.19	0.12	-0.05	0.09						
Asset Equity	0.45	-0.04	0.09	0.09	-0.06	-0.08	0.02	-0.07	-0.03	-0.21	0.17	-0.16	0.09	-0.06	-0.07					
Growth in Sales	-0.05	0.01	-0.09	-0.09	0.01	0.02	0.01	-0.07	-0.07	0.01	0.01	0.11	0.01	0.01	-0.02	-0.02				
RONA	0.03	-0.02	0.01	0.01	0.04	-0.01	-0.01	0.01	0.02	0.05	0.02	0.01	-0.03	-0.03	-0.01	-0.02	0.12			
Current ratio	0.12	-0.21	-0.15	-0.15	0.26	-0.02	-0.01	0.15	0.13	0.59	-0.03	0.37	-0.35	-0.01	-0.01	-0.21	0.01	0.04		
2yr av sales growth	-0.07	0.01	-0.09	-0.09	-0.01	0.03	0.02	-0.07	-0.09	0.01	0.00	0.13	0.03	0.02	-0.02	-0.02	0.71	0.06	0.01	
Max	0.45	0.21	0.97	0.97	0.41	0.48	0.11	0.15	0.13	0.59	0.31	0.56	0.22	0.26	0.48	0.45	0.71	0.12	0.59	0.71
Min	-0.09	-0.21	-0.32	-0.31	-0.08	-0.21	-0.09	-0.17	-0.54	-0.37	-0.24	-0.32	-0.54	-0.17	-0.19	-0.21	-0.09	-0.03	-0.35	-0.09