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Risk-Adjusted Index for Private Equity Evaluation Based of Predictive Firm Characteristics

An empirical study of the public firms taken private by financials buyers from 1997 to 2017 in the U.S.

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Abstract

The objective of this thesis is to assess if there is a risk-adjusted index which could give a better understanding of the opportunity cost for private equity investments. Private equity has become a more professional asset class with heightened attention from long-term investors. The Norwegian Government Pension Fund Global recently assessed the opportunity of moving into unlisted equity, although the proposal was rejected by The Ministry of Finance. Despite the increased attraction to the asset class, there is a persistent lack of consensus on the factors that explain the performance in private equity. In this thesis, we use a predictive model to analyse the pre-transaction financial characteristics of 355 public companies taken private by a PE sponsor. The public-to-private sample is compared to the investable indexes S&P 500, S&P 400 and S&P 600. The indexes function as a market proxies representing distinct market cap segments. The bottom-up analysis seeks to identify if PE funds select targets based on certain characteristics, diverging from the market proxy, which lead to a different exposure to systematic risk factors. We find that PE funds tend to select small profitable firms with conservative capital structures. The findings are seen with regards to the empirical evidence of the level of leverage in buyouts. The implication being that an appropriate investable and risk-adjusted index seem to be a moderately leveraged S&P 600 index.

Contents

List of Abbreviations

AUM	-	Assets Under Management
CAPM	-	Capital Asset Pricing Model
CRSP	-	Center for Research in Security Prices
DPI	-	Distributions over Paid-in Capital
EBITDA	-	Earnings Before Interest and Taxes
ETF	-	Exchange Traded Fund
EV	-	Enterprise Value
GP	-	General Partner
IPO	-	Initial Public Offering
IRR	-	Internal Rate of Return
ISS	-	Composite Share Issuance
KS-PME	-	Kaplan Schoar Public Market Equivalent
LBO	-	Leveraged Buyout
LN-PME	-	Long Nickels Public Market Equivalent
LP	-	Limited Partner
MLE	-	Maximum Likelihood Estimation
NAV	-	Net Asset Value
OLS	-	Ordinary Least Squares
PE	-	Private Equity
PME	-	Public Market Equivalent
PTP	-	Public-to-Private
REIT	-	Real Estate Investment Trust
ROE	-	Return on Equity
S&P	-	Standard & Poor´s
SDC	-	Securities Data Company
TVPI	-	Total Value over Paid-in-Capital
US	-	United States
VIF	-	Variance Inflation Factor

1. Introduction

Private equity is an asset class that became explosively popular during the 1980s, with famous acquisitions such as RJR Nabisco by KKR, which was immortalised through the book Barbarians at the Gate. As of June 2017, private equity assets under management were estimated by Preqin at $2.8 trillion, an all-time high[1]. Meanwhile, dry powder, or uncalled capital, has been on the rise since 2012 and hit a record high of $1.7 trillion in December 2017[2]. Although dry powder has continued to accumulate over the last few years and the industry has witnessed a sizeable growth in allocation, the positive sentiment is expected to persist going forward. A Preqin survey carried out in December 2017 found that 95% of LPs felt that their PE fund investment had met, or exceeded, their expectations over the past 12 months, and that 96% of LPs plan to raise or maintain their long-term PE allocation[1]. Despite the increased interest in the asset class, there is a persistent lack of consensus on the factors that explain the performance in private equity, and how – or if – it can continue to outperform the risk-adjusted returns achieved in public markets. In this paper, we focus specifically on private equity firms investing in the leveraged buyout segment, and we will use the terms private equity and buyout interchangeably.

LPs use a variety of approaches for benchmarking PE performance. The typical approach is to use the IRR, despite its weaknesses, and benchmark the IRR against a broad stock market index such as of S&P 500 or Russel 3000 plus 300 basis points[3]. The risk premium of 300 basis points is considered a fair reward for the increased risk and illiquidity of investing in PE (Appelbaum and Batt 2017). While the methods used by most LPs do include adjustment for the greater risk, it is not as accurate as the PME that is preferred by finance experts who study the issue.

The existing literature on the performance of private equity relative to public markets has primarily used a public index, such as the S&P 500, to adjust IRR into time-weighted returns (Kaplan, 2005). The usage of different types of public market indexes in PME has been challenged in the literature, although there is no clear consensus on which index gives the best representation of the asset class. Harrison, Jenkinson and Kaplan (2014) concluded that PE

[1] 2018 Prequin Global Private Equity and Venture Capital report.
[2] Bain & Company's Global Private Equity Report 2018.
[3] This is an approach widely used by pension funds, i.e. the Oregon Public Employees Retirement Fund (OPERF).

performance has exceeded that of public equities on average, by more than 3% annually. On the other hand, Phalippou (2014) found that after adjustments for size, value and leverage, the average buyout fund underperforms by 3% per annum. How can these two prominent studies reach such different conclusions? The answer to this, as pointed out by Phalippou (2014), is that the choice of public market index is critical. The choice of benchmark should represent the opportunity cost of investing in PE, which is what is lost by not pursuing the next best alternative. The opportunity cost for LPs is the return from the stock market plus a risk premium to compensate for added risk. Our study adds to the literature by aiming to give a better understanding of the underlying characteristics of companies selected by private equity investors, and thereby suggest the appropriate risk-adjusted benchmark for measuring performance. The paper focuses on risk adjustments that might need to be made to get a benchmark that reflects the passive components in private equity returns, which is those elements that could be replicated in the public market at a low cost.

The study use a comprehensive dataset comprised of both public companies and public companies taken private by a PE sponsor over the period 1997 and 2017. We study a sample of 355 public-to-private deals, recognizing that the sample are not completely representative of the full sample. The public companies taken private are likely to be larger than the private targets excluded. To get a sense of the type of companies PE invest into, we compare the characteristics of PE selected companies to companies listed on S&P 500, S&P MidCap 400 and S&P SmallCap 600. We find that the S&P 600 is a better proxy for the PE investment universe as the index better represents the type of companies PE select.

Using S&P 600 as the PE market proxy, we find that PE investors tend to select relatively small firms with little leverage and high profitability. Beta or value proxied by BE/ME or EV/EBITDA are not reliable predictors of PE selection. The results are robust to the use of different regression models. We examine the statistical reliability of our results by splitting the sample into two time-periods: (1) 1997 to 2007 (197 observations) and (2) 2008 to 2017 (179 observations). We find that our results are quite robust over time, and qualitatively similar to the full sample. This suggests that the company characteristics attracting PE firms are stable over time. We assess the sensitivity to the choice of public market index by comparing the results to the use of the investable indexes S&P 500 and S&P 400 as market proxy. Overall, it seems that our findings are robust to the choice of public market index. It strengthens our evidence that PE tend to target small profitable firms with low leverage. In addition, it seems that PE tend to choose growth companies (high EV/EBITDA). However, this finding can be driven by the different sector exposure between PE and public markets.

The findings from our empirical analysis have implications for benchmarking private equity returns. The implication from our findings is that the asset class may exhibit greater risk than the average public listed company. Our most significant finding is that the asset class is tilted towards small companies measured by their market capitalization. We determine the S&P 600 to be a more appropriate public market index in PME calculations. This index better reflects the opportunity cost of investing in PE than the widely used S&P 500. If LPs use the simple PME and compares an investment in PE to an investment in the S&P 500, they will likely overestimate alpha and underestimate the systematic risk. If they instead use the S&P 600 they will likely get closer to the true risk-adjusted returns to private equity. In addition, the index should be leveraged up to reflect the additional leverage PE investors use to finance their acquisitions. A more appropriate index to use in PME calculations is determined to be a levered size adjusted public market index. This index have characteristics that more correctly reflects the risk of investing in PE, and thereby more accurately the opportunity cost. The implication being that when evaluating PE performance, one should carefully consider what the opportunity cost of the investment is, and if there are certain characteristics leading to systematic differences in risk between the two alternatives. Related literature finds that when PE is benchmarked using a levered small cap index as the public market equivalent, PE underperforms public equities.

The remainder of the paper is organized as follows: Section 2 will provide a short presentation of PE and discuss how PE firms create value. Thereafter, theory and related literature will be reviewed in Section 3. Section 4 describes the dataset used for the empirical analysis. In Section 5, we present the methodological approach, descriptive statistics, the variable selection, and the limitation for our thesis. In Section 6, we present our empirical results and in Section 5 we discuss how our findings have implications for benchmarking of PE returns. In the last section, we present our conclusions and prove thoughts for future research.

2. Private Equity

Private equity (PE) refers to investments in equity securities in companies that are not publicly traded on a stock exchange. PE covers investments in venture capital, growth equity, buyout, and turnaround (distress) investments. Our paper focuses on the largest segment – leveraged buyouts. In a leveraged buyout, a company is acquired by a specialised investment firm—generally referred to as a private equity firm—using a relatively small portion of equity and a relatively large portion of debt financing. In this paper, the terms private equity and buyout are used interchangeably. The PE model involves acquiring a large stake of the equity of an unlisted company (the “portfolio company”), and owning it for a limited period (typically 3-7 years), before exiting the company in an IPO, a sale to a strategic buyer, or a sale to another PE firm. During the ownership period, the PE firm tries to increase the value of the portfolio company through active ownership and governance in a way that is difficult to replicate in a public setting. The bulk of investments in PE are undertaken by financial intermediaries referred to as private equity (PE) funds. PE funds are usually organised as limited partnerships with a finite life (10-12 years) managed by PE firms. PE firms raise capital from institutional investors such as insurance companies, pension funds, endowments, sovereign wealth funds, as well as high net worth individuals. Investors in these funds are known as limited partners (LPs). The fund manager, also called general partner (GP), is responsible for sourcing, making and exiting the investments on behalf of the fund. The private equity structure is illustrated in Appendix A, Figure 1.

2.1 How PE Firms Create Value

Private equity is believed to have many unique advantages over public traded equities. PE firms create value by improving operations, advising, monitoring and incentivising management, allowing management to focus on long-term value and securing preferred access to financing. Thus, PE is not a zero-sum game for investors, as it has the potential to create value. On the other hand, investing in public equities is a zero-sum game. Active investment in public equities is about buying undervalued and selling overvalued securities. This amounts to a zero-sum game because in aggregate active investors hold the market portfolio. Hence, the buyer's win tends to be the seller's loss and, as a result, it is questionable whether active equity managers in aggregate add value (see e.g. French, 2008; Fama and French, 2010). The value added to PE portfolio companies does not necessarily mean that the LP get high returns. Investing in PE funds involves high fees for the LP and acquisition premia paid to shareholders in buyouts. The GP is compensated by charging two types of fees to LPs: management fees and performance fees. The management fees is an annual fixed fee usually set to 1.5-2.0% of committed capital, typically intended to cover the fixed overhead costs of a fund´s operations. The performance fee is an additional fee which provides the GP with a share of the profit, depending on fund performance. This profit is referred to as "carried interest," and it is most commonly set at 20% of profits above a hurdle rate. The standard hurdle rate is 8%, which must be realized before the GP receives any carried interest. In addition, GPs also charge additional portfolio company fees, which are partly shared with LPs. The total annual fees paid by LPs is estimated to 5-6%[4], which could offset PE industry´s return edge over public equities. The historical positive industry performance net of fees suggests that there is skill or other premium in PE – the questions is how much is passed on to the end-investor.

Private equity firms create value by applying changes to the companies in which they invest, which Kaplan and Strömberg (2009) categorised into three sets; financial engineering, operational engineering, and governance engineering. Financial engineering is usually seen as the optimisation of capital structure and the minimisation of the after-tax cost of capital. Operational engineering is industry and operational expertise that PE investors use to add value. Governance engineering is the way in which the PE investors control the boards of their portfolio companies and are more actively engaged in the governance than public company boards.

The private equity market has changed dramatically since its inception in the 1980s. The 1980s PE boom was initially focused on highly leveraged capital structures (often relying on junk bond financing) and active governance (Kaplan and Strömberg 2009). Public equities had been equity-dominated, providing plenty of opportunities for leveraged buyout organisations and hostile bidders. Jensen (1989) predicted that private equity would become the dominant organisational structure, partly due to the typical public corporation having low leverage and weak corporate governance. Jensen argued that the PE governance model would be hard to implement in a publicly traded company because of the widely dispersed ownership in public companies. In a leveraged buyout, the PE funds typically acquire a majority stake in

[4] CEM Benchmarking estimate of total annual fee is shown in Exhibit 9 of McKinsey (2017).

the company and hence have voting control. This makes them able to design the corporate governance structure to ensure that the company is run in the interests of its owners. Strong governance gives the PE investor the ability and the incentive to exercise active ownership in the portfolio company. PE firms create the right incentives for employees to act like owners, and they assemble decisive and efficient boards. High-powered incentives are given to management and key employees by requiring them to invest significant amounts of their own wealth in their company's equity (Jensen and Murphy, 1990). Additionally, PE portfolio company boards are smaller and more active than a public company board, which has shown to be more efficient (Yermack, 1996).

In addition to governance engineering, financial engineering was heavily used in the 1980s. It refers to the leverage that is used in connection with the transaction. The use of leverage has mainly two benefits: incentive benefits and interest deductibility (Jensen, 1989). On the other side, if leverage is too high it could lead to financial distress. Leverage is on average higher in PE-backed firms than in public firms. PE portfolio companies can tolerate higher leverage levels as PE investors can infuse more capital when needed to mitigate the risk of distress. Strömberg (2016) found that the presence of a PE investor decreases the expected costs of financial distress, and thus increases the debt capacity of firms. Axelson et al. (2013) study what determines leverage and pricing in private equity buyouts. They point out that over a career executing leveraged buyouts GPs: "arguably make more decisions about firm capital structure than any other agents in the economy," making it reasonable to assume that they should operate close to an optimal capital structure. Axelson et al. (2013) analysed a sample of 1,157 buyouts, and found that credit market conditions is the main explanatory variable for the leverage in buyouts. The evidence suggest that the private equity investor takes on as much debt as they can at any given point of time. The implication is that increased availability of debt financing lead to higher competition, resulting in higher transaction prices, and lower returns.

Jensen (1989) argued that LBOs create value through high leverage and powerful incentives. This was certainly true in the 1980s, when financial and governance engineering were common methods to create value. In the last decades, the focus on creating value through operational engineering has steadily increased. PE firms are building expertise with regard to operational efficiency, and are recruiting industry professionals with an operational background to the advisory board. These professionals are often former executives and consultants. The operational expertise is used to improve the companies in which they invest. Acharya et al. (2009) found that PE firms with professionals with a strong operational background generate a significantly higher return. The PE firm uses the expertise to identify attractive companies, develop value creation plans and implement value creation plans (Strömberg, 2009). A value creation plan could involve cost-cutting, productivity improvements, acquisitions, strategic repositioning, management changes, and upgrades. Overall, the plan is related to finding the best practices with regard to operations.

In recent years, operational engineering has been a more significant alpha generator. These capabilities are much harder to imitate than financial and governance engineering. As the industry has become more mature and competitive, these kinds of engineering are likely to be represented in the transaction price. Thus, to create value, PE firms need to improve the companies in which they invest.

3. Theory and Related Literature

From our understanding of how private equity firms add value, the approach for the risk-adjustment of performance evaluation will be based on the theory related to risk factors, and earlier academic evaluations of private equity performance. The theory and related literature section is intertwined, as the literature covered should be seen in respect to its understanding and consideration of the theories. In this section, the relevant risk factors will be presented. An assessment of risk factors is essential for understanding the potential risk-adjustments necessary to reflect the opportunity cost of PE investments. Earlier academic evaluations of private equity performance will be covered in section 3.2.

3.1 Risk Factors

To understand the systematic risk factors for private equity it is helpful to look at the literature for asset pricing. The basic premise of asset pricing is that the expected return on an asset depends on its systematic risk (undiversifiable risk). The theory states that assets with higher systematic risk should have a lower price, implying a higher expected return. Furthermore, differences in expected returns across assets can be explained by the way in which the assets' return covaries with a number of systematic risk factors. The factors are mainly used in a context related to publicly traded assets, as they are difficult to apply to a large data sample of companies acquired by PE funds through LBOs—due to restricted access to the firm's data. However, by looking at companies acquired by PE funds in public-to-private transactions, we can identify the characteristics of the firm's assets, and adjust the investment returns for loadings on risk factors. The theory behind the risk factors is, therefore, essential for understanding how a benchmark assessing the PE fund's return could be adjusted.

3.1.1 Risk Factors in Public Listed Equities

The most famous and widely used model in asset pricing is the capital asset pricing model (CAPM), introduced in the early 1960s by Treynor (1962), Sharpe (1964), (Lintner 1965), and (Mossin 1966), independently. CAPM is a model that describes the relationship between systematic risk and expected return for an asset. It states that assets that correlate more strongly with the market as a whole carry more risk and thus require a higher return in compensation. The general idea behind CAPM is that investors need to be compensated in two ways: time-value of money and risk. The time-value of money denoted as the risk-free rate (R_f), and the other component represents how much compensation the investor needs to take on additional risk. Beta (β) is the measure of systematic risk. β is defined as:

$$\beta_{\mathrm{i}} = \frac{Cov(R_i, R_m)}{Var(R_m)}$$

where: Cov (R_i, R_m) is the covariance of the asset relative to the market, Var (R_m) is the variance of the market, and β_i= β of asset i. The expected return, according to the CAPM, is then a linear function of the sum of the market risk free rate of interest plus a risk premium, defined as:

$$\mathrm{E(R_i) = R_f + \beta_i(E(R_{m)}\text{-}R_f)}$$

Fama and French (2014) argued that the attraction of the CAPM is its powerfully simple logic and intuitively pleasing predictions about the relationship between expected return and risk. However, the model's empirical record is poor enough to invalidate the way it is used in applications. Fama and French (1993) found that approximating returns by including a SMB factor (small minus big companies) and an HML factor (high minus low book-to-market ratio), in conjunction with the market factor presented by the CAPM, could significantly improve the stock return estimation. Based on this, they demonstrated that stocks with low book-to-market value (value stocks) and stocks with small capitalisation outperform stocks with high book-to-market value (growth stocks) and stocks with high market capitalisation.

$$E(R_i) = R_f + \beta(R_m - R_f) + b_s * SMB + b_v * HML$$

The three-factor model was later expanded into a five-factor model, including a RMW factor (robust minus weak profitability) and a CMA factor (conservative minus aggressive investment), which further improved the estimation of stock returns (Fama and French, 2014).

$$E(R_i) \ = \ R_f + \beta(R_m - R_f) + b_s * SMB + b_v * HML + b_r * RMW + b_c * CMA$$

In the more recent period, a relatively new risk factor has triggered the interest of academics and practitioners. That is the quality factor, which describes the effect of high quality companies outperforming low quality companies in the long term. Quality can be defined in a variety of ways but most commonly by stable earnings growth and low debt. The outperformance of the quality factor is well-documented in financial research (Haugen and Baker, 1996; Sloan, 1996; Asness, Frazzini and Pedersen, 2014; Fama and French, 2015). Risk factors increased in relevance after the publication of a report on the performance of the Norwegian Government Pension Fund (Ang et al., 2009). The authors conclude that much of the active return generated by the fund could be explained by exposure towards well-known systematic risk factors, and in that sense explain the terrible performance the fund experienced during the financial crisis. A description of well-known systematic factors and how they are commonly captured is shown in Table 1 in Appendix B.

Interestingly, while these risk factors have been documented in public equities markets and corporate bond markets, they have not until recently been studied in private equity deals. Andreeva (2017) investigated whether such risk factors are also present in the cross-section of returns in private equity deals. The author provides evidence that the well-documented risk factors in public equities are also present in private equity. Private equity and public equities markets are driven by common underlying effects, which implies that such factors are fundamentally related to the price setting behavior of investors. In the following we will discuss the risk factors in private equity funds.

3.1.2 Risk Factors in Private Equity

The risk factors mentioned in the previous section are all present in publicly listed equities. However, private equity is equity securities in private companies that are not publicly traded. The implication is that PE is an illiquid asset class compared to publicly traded companies. All else being equal, an investor will be willing to pay a higher price for a listed company than an equivalent private company. The illiquid nature of the asset class represents an additional risk as investors who want to sell their investments in bad times must sell at sharp discounts.

There are two types of liquidity risk: market liquidity and funding liquidity (Brunnermeier and Pedersen, 2009). Market liquidity refers to the degree to which an asset can be bought or sold in the market without affecting the asset’s price. Amihud et al. (2005)

provide evidence that stocks with low market liquidity outperform stocks with high market liquidity. The higher the stock market liquidity, the lower the price, and the higher the expected return. The most common liquidity factor is the Pastor and Stambaugh liquidity factor, which represents an asset's sensitivity to the aggregate stock market liquidity. Funding liquidity relates to the risk that arises when an investor has to meet their obligations and refers to how easily the investor can obtain financing for their investments. The funding risk is the most relevant liquidity risk for investors in PE (LPs) as these investors primarily invest through PE funds. GPs can call committed capital whenever the GP wants to invest. Thus, the LPs need to have liquidity available so that future capital calls can be met. However, this funding risk can be managed through vintage diversification[5].

While private equity is exposed to funding liquidity risk, it is also exposed to many of the same systematic factors as public equities, as previously mentioned. An illustration of this is that PE funds can buy and sell companies by delisting and listing these on a stock exchange. This implies that both after and before the firms are owned by the PE fund, the assets are considered as public equities. The research on risk loadings for private equity is relatively recent. The general idea is to estimate the sensitivity of the PE market with respect to well-known systematic risk factors. Because private equity investments lack continuous market prices, we cannot compute time series of returns, which are commonly used in the traditional time-series approach to estimate factor loadings. The return series are created using different data sources as well as different methods to convert the data to return-like series. Some use the gross returns of individual PE deals, while others use net cash flows to PE funds. The two common methods to estimate factor loadings are to use: (1) one-step regressions contemporaneously and lagged risk factors to estimate risk loadings[6] and (2) estimation of discount rates of private equity returns from cash flows accruing to LPs[7]. The empirical findings diverge from these two methods. Table 1 below summarises the papers estimating risk loadings in PE.

[5] Vintage diversification refers to an LP committing to several PE funds of different vintages.
[6] See Pedersen, Page and He (2014); Fan, Fleming, and Warren (2013); Barber and Wang (2013); Ewens, Jones, and Rhodes-Kropf (2013).
[7] See Ang, Chen, Goetzmann, and Phalippou (2013); Franzoni, Nowak, and Phalippou (2012); Driessen, Lin, and Phalippou (2012).

Table 1
Summary of Papers Estimating U.S. Buyout Factor Sensitivities

The table illustrates U.S. buyout factor loading estimates found in the literature. The factor loadings are rounded to increments of 0.05.

Authors	Market Beta	Small (SMB)	Value (HML)	Illiq. (P-S)	Remarks
Franzoni et al. (2012)	1.0-1.3	insignificant (-)	0.7-1.0	0.6	Individual deal/before fee and carry
Axelson et al. (2014)	2.2-2.4	N/A	N/A	N/A	Individual deal/before fee and carry
Jegadeesh et al. (2015)	0.9-1.1	0.6	0.8	N/A	Individual deal/before fee and carry
Driessen et al. (2013)	1.3-1.7	insignificant (+)	insignificant (-)	N/A	Net cash flows/after fee and carry
D-S (2018)	1.2-1.4	insignificant (+)	0.7-0.8	insignificant (-)	Net cash flows/after fee and carry
Ang et al. (2017)	1.2-1.3	insignificant (+)	0.6-0.7	0.6	Net cash flows/after fee and carry

The literature generally finds evidence of PE exhibiting high market beta. Beta tends to be higher when factor loadings are estimated using gross returns rather than returns after fees and carry, the reason being that carry will reduce net returns to LPs when gross returns are positive, but not when they are negative[8]. Hence, carry payments reduce the market beta. Furthermore, the evidence suggests that PE is exposed to value companies instead of growth companies. On the contrary, there seems to be little evidence of exposure to small companies. Finally, PE tend to be exposed to the P-S liquidity factor.

Overall, the findings suggest that PEs have different loadings on public equity risk factors, the implication being that PE should have higher returns than public markets on average, as the asset class as a whole is exposed to systematic risk factors. A potential reason for different loading is that the characteristics of PE-backed companies differ systematically from public companies. Buyouts tend to invest in mature profitable companies with positive cash flow. Stafford (2017) showed that PEs tend to invest in companies that are smaller and have higher leverage, higher BE/ME, lower beta, lower EV/EBITDA and lower profitability. Rasmussen and Chingono (2015) found that buyouts are just "small-value on steroids." However, L'Her et al. (2016) found that PE is tilted towards small-cap, but not value. The implication from these findings is that PE returns and risk can be replicated in public markets by investing in securities that load on the same systematic factors. However, if markets are "incomplete," PE returns could not be mimicked by investing in similar listed companies. Ang et al. (2018) found that private equity returns are only partially spanned by public equity returns. Thus, PE could be affected by systematic risk factors that are not present in public markets. In order to invest in PE, investors would require a premium. The exposure to public equity risk factors needs to be accounted for when evaluating the relative performance of

[8] Døskeland and Strömberg (2018).

private equity compared with benchmarks representing public equities. Buyout funds should not be rewarded for earning higher returns simply because they buy companies exposed to systematic risk factors. Exposure to factors such as size and value can be bought directly at negligible cost. Thus, there is no need to pay high fees for it. In the next section we will present common methods for the benchmarking of private equity.

3.2 Benchmarking

While it is widely acknowledged that the top quartile PE managers generate alpha for LPs net-of-fees, diverse evaluation metrics allow half of all PE funds to call themselves top-quartile (Harris-Stücke, 2012). We believe that an adjusted public benchmark would be better suited for capturing the risk-adjusted return for private equity. Benchmarking is based on historical returns and is thus no guarantee for future returns. PE is an asset class for which it has been proven that managers have a certain persistence in returns (Kaplan and Schoar, 2005), although Harris et al. (2014) found that the performance persistence of buyouts has gone down. A risk factor-adjustment benchmark providing a more robust evaluation metrics—compared to metrics such as IRR—could also be relevant for fund selection, although it is not the main objective of our study, and the benchmark will focus on the asset class rather than fund selection. A risk-adjusted benchmark should thus be considered a useful tool for the LPs, and the ones evaluating their performance, to see if they are obtaining satisfactory returns from their PE investment strategy, or if similar gross returns could be obtained at a much lower cost in the public markets. We would like to emphasise that obtaining similar gross returns is not necessarily as easy as being exposed to assets with similar risk factors, and that private equity, not being a zero-sum game, might make it more attractive for certain investors; in particular, long term institutional investors.

The two main indicators used by the private equity industry to assess the absolute performance of a fund's investments are the Internal Rate of Return (IRR) and the market multiples. IRR is commonly used amongst practitioners. IRR is defined as the discount rate that equates the net present value of all outflows and inflows related to a specific fund to zero. The argument for deeming IRR an appropriate performance measure is that IRR takes into account the irregular nature of cash flows of private equity investment, considers the time value of money, is relatively easy to calculate, and can be straightforward to interpret.

However, Phalippou (2008) illustrated how average IRRs were significantly biased upwards if IRR and duration were correlated—a possible explanation for so many managers and investors reporting high performance. Performance "multiples" can be divided into the investment multiple and the realisation multiple. The investment multiple, also known as the total value over paid-in capital (TVPI) multiple, is defined as the sum of all cash distributions plus the latest NAV, divided by the sum of all takedowns. The realisation multiple, also known as the distributed over paid-in capital (DPI) multiple, is defined as the sum of all cash distributions divided by the sum of all takedowns. A shortcoming of TVPI and DPI is that they do not account for the time value of money.

The IRR and multiples are applicable for comparing the performance of private investments, but not for comparing with other asset classes that use time-weighted rate of returns, such as public market returns. Public Market Equivalent (PME) is a set of analyses designed to benchmark a private investment against a public benchmark or index. It makes it possible to apply the opportunity cost argument—that the performance of an investment in private equity should be compared to the investor's next best alternative. Long and Nickels proposed the first PME analysis in 1996 (Long & Nickels, 1996). The Long Nickels PME returns an IRR. Long and Nickels' PME analysis is based on Bailey's framework (Bailey, 1992), which identifies the six qualities required for a valid benchmark: unambiguous, investable, measurable, appropriate, reflective of current investment opinions, and specified in advance. They found that an index return comparison (later known as LN-PME) using the S&P 500 index fulfilled all quality characteristics except for "appropriate". In this context, Bailey (1992) defined appropriate as: "*The benchmark chosen should be consistent with the style of the investment manager whose performance is being gauged."* Although the PME method using the S&P 500 fulfils most of the required qualities, we raise certain concerns regarding the similarity in risk exposure for the index.

The most widely used form of PME in more recent academic literature is the KS-PME, initially presented by Kaplan and Schoar (2005). The method discounts both capital calls and distributions by returns from a public equity benchmark index. The KS-PME is then calculated as the ratio between the sum of discounted distributions and the sum of discounted capital calls, defined as:

$$KS - PME = \frac{FV\ (distributions)}{FV(calls)}$$

The numerator captures the wealth an investor would have obtained by investing in the PE fund, while the denominator captures the wealth the investor would have obtained by investing in the benchmark index. A KS-PME above one implies that the PE strategy yielded a higher return than the benchmark index. The rate used to discount the cash flows can be thought of as the opportunity cost of the investment. The PME ratio represents how many dollars needed to be invested in the benchmark for each dollar in the buyout fund. While the aforementioned LN-PME returns an IRR with a negative NAV limitation, the KS-PME returns a market multiple. As with the TVPI and DPI multiples, the KS-PME is not straightforward to translate into a yearly excess return. The Direct Alpha, introduced by Gredil et al. (2014), provides the IRR equivalent to KS-PME. It is deducted from the KS-PME calculation by computing an IRR using the discounted calls and contributions, and taking the natural logarithm. The Direct Alpha formula is derived from the definition of α in modern portfolio theory.

The existing literature on the performance of private equity against public markets has used a public index such as the S&P 500, to adjust IRR into time-weighted returns (Kaplan, 2005). The usage of different types of indexes in PME calculations has been challenged in the literature, although there is no clear consensus on which index gives the best representation. Harrison, Jenkinson and Kaplan (2014) concluded that PE performance has outperformed public equities on average, by more than 3% annually. However, Phalippou (2014) found that after adjustments for size, value and leverage, the average buyout fund underperforms by 3% per annum. As with all investments measured in relative terms, the choice of benchmark is critical for performance.

3.3 Performance Measurement Issues

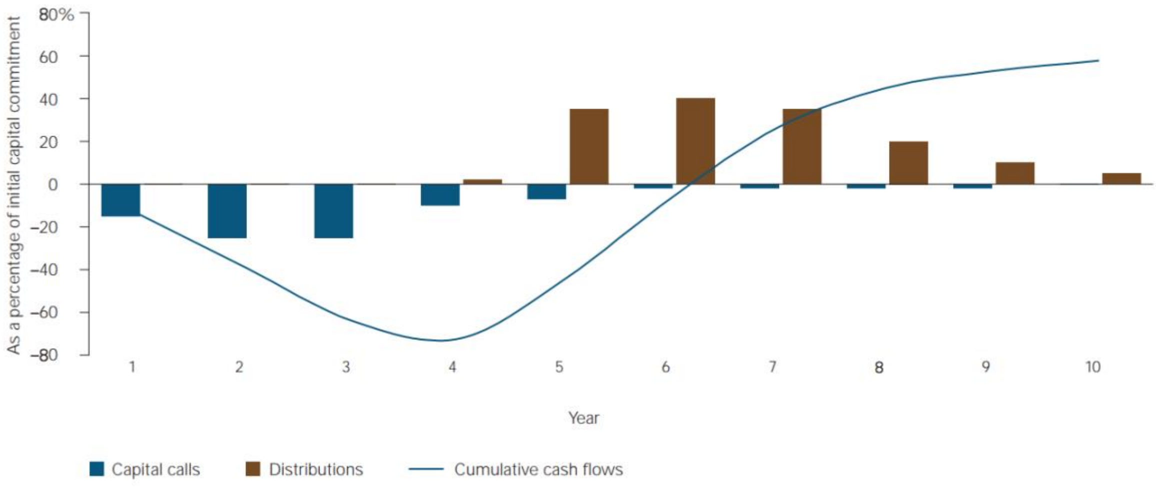
The lack of continuous market prices for PE poses challenges when evaluating performance. In particular, the ultimate performance of a PE fund investment is only known when the fund is fully liquidated (usually 10 years). In the interim period, the PE returns are based on quarterly reported Net Asset Value (NAV). The reported NAV calculations pose several challenges for comparisons with public equities. The use of NAV can lead to stale pricing, whereby fund managers assign old values to the investments even if evidence of changes in value exists. This leads to the potential for highly smoothed returns, and does not give an accurate view of the true underlying performance prior to exit[9]. Smoothed returns hinder traditional risk adjustment, and therefore govern how the PE performance is interpreted. The discretion in marking the portfolio NAV is likely to lead to downward biased estimates of risk and destroy the covariance structure in returns.

Besides the difficulty with regard to how returns are calculated, the performance returns for the asset class can be difficult to obtain. Some researchers have, therefore, used proprietary data (see Robinson and Sensoy, 2013; Axelson et al. 2014), which makes the results difficult to replicate. The most recent research is mainly based on the commercially available databases Burgiss, Cambridge Associates, and Preqin. Harris, Jenkinson and Kaplan (2014) compared the commercial databases and found that the returns from the newer datasets – Burgiss, Cambridge Associates, and Preqin – are generally consistent with each other, while the returns from the earlier Venture Economics datasets appear to be biased downwards. The Venture Economics database is, therefore, used less frequently in newer research, and early research needs to be treated with consideration as to how the interpretation is affected. Better commercially available performance data makes the benchmarking of PE as an asset class a more reliable metric for asset allocation.

Another issue in regard to measuring performance arises due to the irregular timing of cash flows, called the J-curve effect. The J-curve refers to the pattern whereby the PE fund net cash flow is negative early in the fund´s life and positive later on, which is illustrated in Figure 2. The cash flow is negative early on because the committed capital is invested in portfolio companies. In addition, GPs´ charge management fees of 1.5-2.0% on committed capital. Once the portfolio companies are exited the cash flow turns positive as the proceeds are returned to LPs. The implication is that time-weighted performance measures commonly used to calculate returns in public securities are no longer appropriate.

[9] This is reflected in a quote from David Swensen, chief executive officer of the Yale University endowment: “Illiquidity masks the relationship between fundamental drivers of company values and change in market price, causing private equity’s diversifying power to appear artificially high.”

Figure 2
J-Curve
The figure illustrate the J-curve effect - the irregular timing of cash flows. Figure adapted from Gilligan and Wright (2010).



3.4 Why a Risk-Adjusted Benchmark?

The review of related literature has left us with a foundation to build our research upon. Despite the increased importance of the asset class, surprisingly there is a persisting ambiguity in regard to PE performance relative to public equities. Harrison, Jenkinson and Kaplan (2014) concluded that PE performance has outperformed public equities. On the other hand, Phalippou (2014) found that after adjustments for size, value and leverage, the average buyout fund underperforms. How can these two prominent studies reach such different conclusions? The answer to this, as pointed out by Phalippou (2014), is that the choice of benchmark is critical. A better understanding of the appropriate risk-adjusted benchmark for measuring the opportunity cost of an investment in PE is critical to measuring its performance. The thesis adds to the literature by aiming to give a better understanding of the appropriate risk-adjusted benchmark for measuring the opportunity cost of an investment in PE.

4. Data

In this chapter, data sources, sample selection and inclusion criteria are explained. In addition, both the strengths and weaknesses of our dataset will be elaborated. The variable selection, to which the inclusion criteria are applied, is explained in Section 5.3. The variables examined in Section 5.4 are: market beta, sales, market capitalisation (ME), EV/EBITDA, book-to-market ratio (BE/ME), debt to total value (D/V), EBITDA/Sales, debt to enterprise value (D/EV), and debt to EBITDA (D/EBITDA). In this chapter, we will apply specific inclusion criteria to EBITDA and BE/ME, and a general inclusion criterion where observations with missing variable data are excluded.

4.1 Sample Selection

To conduct the empirical analysis, we need a comprehensive dataset comprised of both a sample of public companies functioning as the market proxy (non-target sample) and a sub-sample of public companies being taken private by a financial buyer through a leveraged buyout (target sample). Our sample selection primarily relies on four commercial databases: Securities Data Company (SDC) Platinum, Bloomberg, The Center for Research in Security Prices (CRSP), and Compustat[10].

The target sample is meant to be representative of the characteristics of the companies targeted by buyout PE funds. The sample is by no means perfect, as we have excluded private-to-private transactions. Despite the impediment, we believe that it is an adequate PE market proxy. The dilemma is discussed in detail in Section 4.4.

For the non-target sample, we are interested in finding an investable index which could function as a public market proxy. The S&P 600 (small cap), S&P 400 (mid cap), and S&P 500 (large cap), indexes were used in the analysis as they represent different market size segments and are recognisable to investors, and also for simplicity. Some concerns regarding the S&P samples will be raised under Section 4.4 Strengths and Weaknesses. The analysis will mainly be based upon the findings for S&P 600 as the market proxy, which rationale are explained in Section 5.2.1.

[10] CRSP and Compustat are accessed through Wharton Research Data Services (WRDS).

4.2 Target Sample

The sample of public targets taken private comes from the SDC Platinum database. Mergers and acquisitions with announcement dates between 1997 and 2017 are selected. The sample is constructed by employing seven filters. We include transactions in which: (1) the target firm is U.S. based; (2) the deal is a leveraged buyout; (3) the target is going private; (4) the acquiring firm is a financial buyer; (5) the transaction results in at least 80 % ownership of the target firm; (6) financial firms are excluded; (7) the deal is completed (see Appendix C, Table 1 for SDC search filters). Our requirements provide a sample of 546 deals over the period from 1997 to 2017, which are reduced to 355 deals after the implementation of the inclusion criteria mentioned below.

Financial firms are excluded from the sample (filter 6) because high leverage in these firms is likely to have a different implication than for non-financial firms, where high leverage is more likely to indicate distress (Fama and French, 1992). Hence, financial firms with SIC-codes between 6000 and 6799 are excluded from the sample. Additionally, to address the issue of certain firms with missing SIC-codes, we exclude firms that have names including “bank, banc, insurance, REITs, finance, financial.”

Despite the relatively high quality of the data, several difficulties are associated with using the data. Many of the deals have missing pre-transaction information. We merge the sample with Compustat for added pre-transaction financial data on the targets. As a last resort, we also collect some missing financial data from annual reports. Historical prices and return data for each company are retrieved from the CRSP database by matching the targets company identifier from SDC Platinum[11]. The first inclusion criterion is that only observations where we are able to identify complete variable information, given our variable selection in Section 5.3, are included.

Consistent with previous research (e.g. Fama & French, 1992) observations with negative BE/ME are excluded. A reason for the exclusion is the assumption that shareholders cannot have negative value because of a company’s limited liability structure. The sample

[11] There is no similar unique permanent security identifier number for SDC Platinum and CRSP. Attempts were made to match the companies in the databases through several operations, as we rely on security identifiers from SDC Platinum which are not permanent (CUSIP and Ticker) and/or not unique (Ticker). We were able to get the PERMNO code through these matching operations, which is a unique and permanent security identifier. For each company, the PERMNO code has been validated by matching the company name, and by confirming a short range between the last return date and the transaction date.

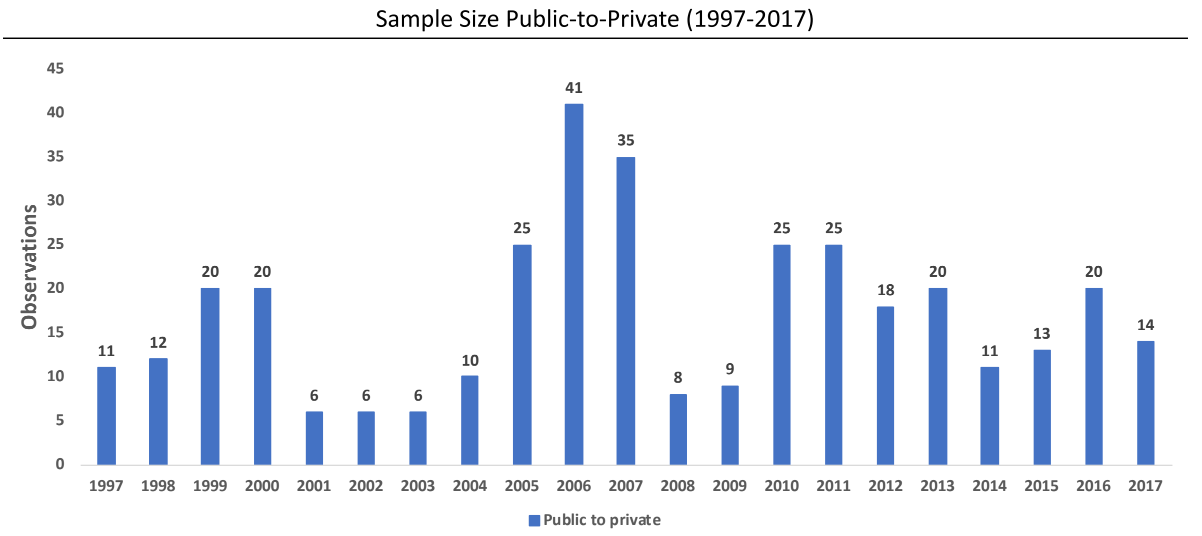
contain few observations with negative BE/ME; discarding these observations should, therefore, have limited impact on the results. Furthermore, numerous target companies report highly negative EBITDA. These companies are often characterized by low enterprise values, leading to extreme multiples and a potentially strong impact on the results if not excluded. Therefore, companies with negative EBITDA are excluded from the sample. To summarise, the aggregated effect of the inclusion criteria restricts the dataset sample to 355 companies over the period from 1997 to 2017, implying an average of 17 observations per year.

The inclusion criteria are quite strict, meaning that we have likely excluded a large part of the period´s public-to-private transactions compared to some of the earlier research looking at similar data (e.g. Strömberg, 2008; Kaplan and Strömberg, 2009; Stafford, 2017[12]). Strömberg (2008) and Kaplan & Strömberg (2009) impute missing enterprise value using a Heckman (1979) maximum likelihood estimation. However, for the period we estimate that there are sufficient observations preserved to avoid this method. Since it is difficult to assess why some companies have missing information, it is challenging to evaluate whether any bias is introduced. We assume that the missing data is not due to some underlying characteristics but random, and therefore, dropping them will not create any bias.

The distribution of the number of deals in the sample over time is illustrated in Figure 3. The figure depicts a large variation in the number of deals per year. Despite possible distortion due to data availability, a cyclical pattern can be observed in the distribution of public-to-private targets over time. This is consistent with conventional wisdom among scholars and practitioners in that PE investments are cyclical[13]. Several factors come into play when PE firms make investments, and one of them is market timing (Kaplan & Stromberg, 2009).

[12] Stafford (2017) does not explicitly address the issue of missing values in the public-to-private sample. Only the pre-exclusion sample size of 711 deals collected from the Thompson Reuters Merger and Acquisition database is mentioned.

Figure 3
Sample Size
The table show the number of observations of the public-to-private sample over the period 1997 to 2017.



4.3 Non-Target Sample

The three non-target samples, functioning as public market proxies, are the constituents of the investable indexes: S&P 500, S&P 400, and S&P 600. The data for the non-target samples are collected from the Bloomberg Terminal. As the constituents of the indexes can vary between each year, we downloaded financial information for each individual year from 1997 to 2017. To be consistent with the inclusion criteria applied for the target sample, we exclude financial firms, companies with negative BE/ME and EBITDA, as well as companies with missing variable values.

The main regression in the results uses the S&P 600 as the non-target sample. The data collected from the Bloomberg Terminal results in 12.602 observations for the S&P 600. The elimination and restriction criteria reduce the non-target S&P 600 sample to 6.514 observations over the period from 1997 to 2017.

Figure 4
Sample Size
The table show the number of observations of the S&P 600 sample over the period 1997 to 2017.

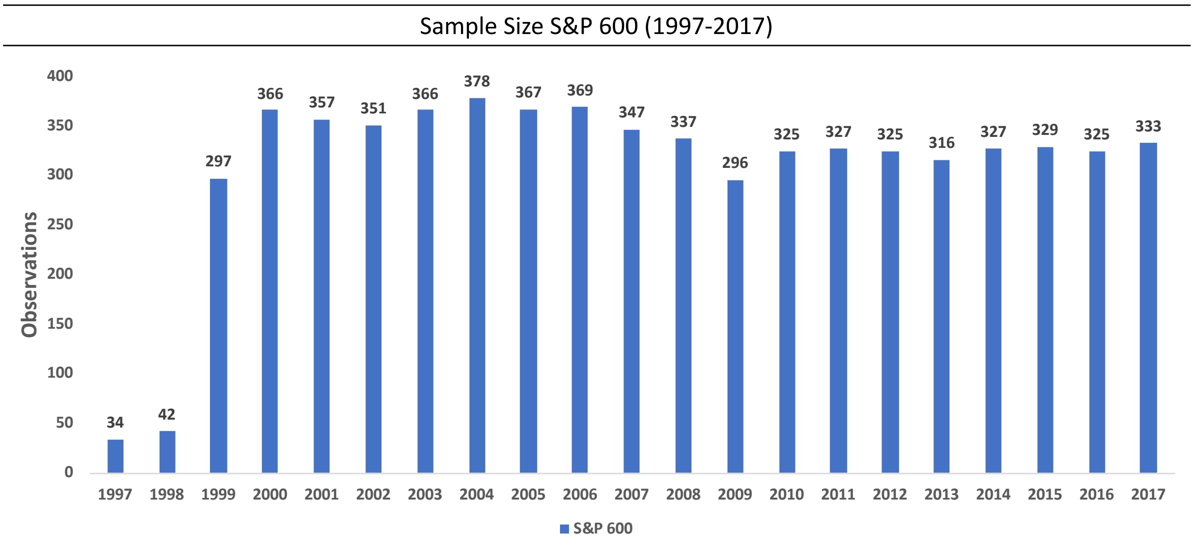


Figure 4 reveals a substantial improvement in the S&P 600 data from 1999 onwards. The number of firms in the sample does not increase monotonically over time. The variation in each year could be caused both by the number of financial firms (which are excluded from the sample) and the availability of the required data variables over time. The number of observations for S&P 500 and S&P 400 is depicted in Figure 1 and Figure 2, respectively, in Appendix D.

4.4 Strengths and Weaknesses of the Dataset

To assess the pre-transactional financial characteristics of PE targets against a public market proxy, we follow the approach whereby a sub-sample of public equities that have been taken private by a financial buyer is studied. Consequently, the assumption we make is that the public-to-private deals are a good proxy for the private equity market. Based on the number of LBO deals between 1970-2007, public-to-private deals account for 6.7% of all LBO transactions (28.2% adjusted for EV), private-to-private account for another 46.8% (21.8% adjusted for EV), while the rest of the deals are divisional buyouts, financial vendor or distressed (See Strömberg, 2008, Table 2A). For the assumption to hold, PE investors should target companies with certain characteristics, independent of the company being private or public. Although we identify the characteristics pre-transaction in this study, the assumption relies on similar characteristics after the completion of the acquisition. It is because specifications in the transaction, such as the amount of debt used, can lead to changes in the systematic risk exposure due to the effect of leverage on market beta. Based on findings in earlier studies (e.g. Phalippou, 2014; Strömberg, 2008) private-to-private deals seem to at least be weighted differently on the size factor by targeting smaller companies. Ideally, we should include private-to-private deals to give a more complete representation of the investable PE market, and control for the possibility of PE funds having potentially different selection criteria for private companies.

Unfortunately, sufficient data on private companies is not available as private companies are not required to disclose financial information to the public. The SDC database includes some information on private-to-private transactions, but much of the data needed to fit the private-to-private deals into our model are missing. To illustrate, Strömberg (2008) looked at private equity buyout characteristics at the transaction date and found that in the CapitalIQ database, the enterprise value is missing for buyouts of independent private companies in 69% of the transactions. Furthermore, the variables we rely on in this analysis are dependent on market pricing and volatility. Such information could be derived from public comparable, with potential adjustments for leverage and other characteristics. However, the assumptions that need to be made to make private-to-private buyout data useable in our model would lead to great uncertainty, and further call into question the reliability of our estimates. As a result, we rely on public-to-private transactions to analyse the characteristics of PE targets.

The second implication for our dataset is based upon the time-period. By looking at the period 1997-2017, we have excluded two historical PE periods. As mentioned in Section 2.1; in the 1980s, U.S. public equities were heavily equity-focused, and the PE boom was largely focused on generating returns through highly leveraged capital structures (Kaplan and Strömberg, 2008). Since we are interested in finding support for the opportunity cost for PE investments in the present time, we consider the exclusions a strength, rather than a weakness, as it might lead to inaccurate predictions of present characteristics for target companies. The period preceding the PE boom, between 1990 to 1996, is characterized by few public-to-private buyouts (29 observations before inclusion criteria). Few observations each year gives more power to each individual deal, which could lead to unreliable estimates, and the deals for the period between 1990 to 1996 is, therefore, not included in the data sample.

5. Methodology

There is little empirical evidence on the asset selection of buyout funds. Stafford (2017) found evidence supporting the notion that PE firms do not choose their targets randomly, but target certain characteristics. This empirical study uses a multivariate logistic regression model to determine a functional relationship between firm characteristics and public-to-private likelihood. The objective is to investigate whether there exist significant differences between public-to-private and public listed companies which have significance for the risk-adjusted returns. The findings will lay the foundation for our suggestion for a public stock market index, tailored to better match the characteristics of PE buyout investments, which could provide a more accurate measure of the risk-adjusted returns of the asset class.

In this chapter, the methodology will be presented. First, we will introduce the multivariate logistical regression model. Then, the comparison between the target sample and the three different non-target samples—introduced in Section 4.1—will be presented in the descriptive analysis. The descriptive analysis has implications for the choice of the public market index employed in the main regression in Section 6.1. Additionally, we will devote a section to the explanation of the variable selection which is customised with respect to the objective—including the variables that could help explain variations in systematic risk exposure. Finally, other factors that could have implications for the model, and the findings in Section 6.1, will be discussed in Limitations.

5.1 Methodological Approach

In this section, the logit model will be presented.

5.1.1 Multivariate Logistic Regression Model

We use a logit model to empirically test the predictors of whether a company is taken private, backed by a PE fund. A logistic regression model allows for an empirical assessment between the binary outcome variable and a group of predictor variables. It overcomes the limitations of the linear probability model by condensing the probability to a value between zero and one[14].

$$L = \ln\left(\frac{p}{1-p}\right) = b_0 + b_1X_1 + \ldots + b_nX_n \qquad (1)$$

$$where\ p_i = \Pr(Y_i = 1)$$

$$p_i = \Pr(Y_i = 1|\boldsymbol{X_i}) = F(b_0 + b_1X_1 \ldots + b_nX_n) = \frac{1}{1+e^{-(b_0+b_1X_1 \ldots + b_nX_n)}} \qquad (2)$$

The logistic model is estimated according to Equation 1 by using various financial characteristics as discriminators between target and non-target firms. The logit model is nonlinear in the coefficients, and the parameters are estimated using the maximum likelihood estimation (MLE)[15]. The MLE consists of the values of the coefficients that maximise the likelihood function. MLEs are the values of b_0, b_1,…,b_i most likely to have produced the data. The estimated probability (p_i) in Equation 2 is the estimated probability of an individual company being taken private.

The estimated coefficients are interpreted as the change in log-odds associated with a one unit change in the independent variable, ceteris paribus. This makes the interpretation of the regression coefficients in Equation 1 difficult. These coefficients are therefore often converted into an odds ratio by exponentiating the coefficient. Odds ratios in logistic regression can be interpreted as the effect of a one unit of change in the independent variable on the predicted odds ratio, holding all other variables constant. The sign of the coefficient in Equation 1 tells us whether the probability of a company being taken private will increase or decrease. The interpretation is that an increase in an independent variable will make the likelihood of the dependent variable more or less likely. However, we cannot directly interpret the magnitude of the estimated coefficients. In this thesis, we are interested in the characteristics of public-to-private companies compared to public companies. The estimated coefficients are not used to build a model to predict possible public-to-private targets. Hence,

[14] The linear probability model could give predicted probability above 1 or below 0 (Stock & Watson, 2011).

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

we are just interested in the sign and statistical significance of the estimated coefficients. Further description of the logistic regression model is provided in Appendix E.

5.2 Descriptive Analysis

In this section, we provide a descriptive overview of the explanatory variables in the study. In Section 5.1, the characteristics of the targets are assessed by comparing the PTP sample to the three different control groups, comprising of the S&P 500/400/600 indexes. Each index serves as a market proxy for its respective market capitalisation segment. In Section 5.2, the PTP sample will be compared with S&P 600 which is considered the best PE market proxy.

5.2.1 Descriptive Statistics for All Samples

To begin our exploration of possible differences in systematic risk between private equity and public equity, we turn to the descriptive statistics of Table 2. This table shows mean and median values of the explanatory variables in the PTP sample and each of the public market samples. The time-period examined is 1997 to 2017.

Table 2
Descriptive Statistics

This table shows mean and median for each variable in our sample for the period 1997 to 2017. Measures are beta, ME, Sales, EV/EBITDA, BE/ME, EBITDA/Sales, D/V, D/EBITDA and D/EV. ME and Sales are measured in millions of 2017 USD.

	Public-to-Private		S&P 600	
	Mean	Median	Mean	Median
Beta	1,12	1,01	1,12	1,05
ME	2 104	519	1 094	913
Sales	1 867	507	1 410	923
EV/EBITDA	18,98	9,43	15,95	9,52
BE/ME	0,65	0,53	0,61	0,50
EBITDA/Sales	0,16	0,13	0,15	0,12
D/V	0,20	0,14	0,22	0,18
D/EBITDA	2,42	1,53	3,52	1,82
D/EV	0,22	0,16	0,24	0,20

	S&P 400		S&P 500	
	Mean	Median	Mean	Median
Beta	1,09	1,03	1,00	0,94
ME	3 441	2 977	31 480	13 252
Sales	3 558	2 369	20 920	9 468
EV/EBITDA	14,41	9,61	13,36	9,97
BE/ME	0,50	0,43	0,41	0,34
EBITDA/Sales	0,19	0,15	0,21	0,19
D/V	0,23	0,19	0,22	0,18
D/EBITDA	3,13	1,93	2,93	1,87
D/EV	0,25	0,21	0,24	0,19

The most striking features of the different samples is the discrepancy in size, as proxied by ME and Sales. The S&P 500 sample has a inflation-adjusted median market capitalisation of $13.3 billion. In comparison, our PTP sample has a inflation-adjusted median market capitalisation of $519 million. The largest PTP buyout for the period was TXU Corporation at $44 billion pre-announcement, while 11 of 355 buyouts were larger than the S&P 500 median for their respective year. S&P 500 (as well as the other S&P indexes) is an active index, in the sense that its inclusion criteria are based upon a size metrics, effectively including large cap companies. The market capitalisation threshold for S&P 500 is currently $6.1 billion[16]. 28 out of 355 companies in the PTP sample would have been above that minimum threshold.

Our public-to-private sample represents some of the larger private equity buyouts. Earlier research has been widely based upon S&P 500 for measuring performance with KS-PME, including Jenkinson et al. (2015), Brown et al. (2015), Robinson and Sensoy (2016). In addition, Bain's annual Global Private Equity Report based its PME calculations on S&P 500 for the U.S. market. Using the S&P 500 index in PME calculations is an effortless approach, as it is a widely used and recognised benchmark for publicly traded U.S. equities. Brown et al. (2015) justify their usage of the S&P 500 in their PME calculations based on the fact that it is "a widely used proxy for U.S. public market returns and allows for direct comparison to past research." Based upon an assumption of an existing size risk premium in the U.S. equity market, the arguments about S&P 500 being a widely used proxy for U.S. public market returns are not sufficient to defend the use of a sample of companies substantially larger than those acquired by private equity buyout funds. S&P 500 is a large capitalization index, and as it does not seem to reflect the size segment of the great majority of deals in the PE investment universe, we do not consider it as the most appropriate investable index to use when considering a risk-adjusted benchmark.

Most studies have confirmed that the firm PE funds invest in are usually small (e.g. Phalippou, 2012). The S&P 600 provides investors with a benchmark for small-sized companies. The index is distinct from the large-cap S&P 500 and mid-cap S&P 400, and reflects the distinctive risk and return characteristics of the small-cap segment. The median inflation-adjusted market cap is $519 million in the PTP sample, and in comparison $913 million for the S&P 600 sample. This suggests that PE invests in the bottom half of the small-

[16] S&P U.S. Indices Methodology, April 2018. https://us.spindices.com/documents/methodologies/methodology-sp-us-indices.pdf

cap index. The S&P 400 is not a justifiable market proxy for the benchmarking of private equity. Seen in comparison to the S&P 600, the mid-cap index is too large to reflect the size of the private equity investments. Furthermore, since the S&P 500 is one of the most widely used equity indexes in the United States, and a frequently used benchmark for U.S. equity investments, there should be some good justifications for using the S&P 400 instead.

To conclude, we believe that a small-cap index would better reflect the companies most PE managers target. When benchmarking, it will be important to benchmark against public companies of similar size. The small-cap S&P 600 will therefore be used as the public market proxy in the rest of this study.

5.2.2 Descriptive Statistics for PTP and S&P 600

Summary statistics for the PTP sample and the S&P 600 sample are shown in Table 3. The full sample is comprised of 6865 observations, where 355 observations is from the PTP sample and 6510 from the S&P 600 sample. Even though we have excluded the most extreme values from the dataset, the average between the two groups still deviate from each other[17]. However, when focusing on the median, the deviation is much smaller.

Table 3
Descriptive Statistics

This table shows summary statistics for the PTP sample and S&P 600 sample. Measures are beta, ME, Sales, EV/EBITDA, BE/ME, EBITDA/Sales, D/V, D/EBITDA and D/EV. ME and Sales are measured in millions of 2017 USD.

Public-to-Private						
	Observations	Mean	Median	Min	Max	SD
Beta	355	1,12	1,01	-0,32	5,06	0,77
ME	355	2 104	519	5	37 955	4 778
Sales	355	1 867	507	25	61 645	5 342
EV/EBITDA	355	18,98	9,43	0,40	1 101,46	80,45
BE/ME	355	0,65	0,53	0	4,71	0,54
EBITDA/Sales	355	0,16	0,13	0	2,61	0,16
D/V	355	0,20	0,14	0	0,90	0,20
D/EBITDA	355	2,42	1,53	0	71,59	4,74
D/EV	355	0,22	0,16	0	1,06	0,22

S&P 600						
	Observations	Mean	Median	Min	Max	SD
Beta	6 510	1,12	1,05	-1,08	8,96	0,66
ME	6 510	1 094	913	34	6 482	772
Sales	6 510	1 410	923	27	22 750	1 700
EV/EBITDA	6 510	15,95	9,52	0,30	5 003,79	86,31
BE/ME	6 510	0,61	0,50	0	6,98	0,48
EVITDA/Sales	6 510	0,15	0,12	0	0,96	0,11
D/V	6 510	0,22	0,18	0	0,97	0,19
D/EBITDA	6 510	3,52	1,82	0	1 475,08	26,81
D/EV	6 510	0,24	0,20	0	1,86	0,21

[17] See Section 5.3 for discussion and exclusion of outliers.

We still observe a large variation in the market capitalisation between the samples. The average inflation-adjusted market cap is $2.1 billion in the PTP sample, and in comparison $1.1 billion for the S&P 600 sample. This indicates that PE target large companies. However, when looking at the median inflation-adjusted market cap the PTP sample displays smaller values. The S&P 600 sample has an median inflation-adjusted market capitalization of $913 million. In comparison, our PTP sample has an inflation-adjusted median market cap of $519 million. The huge difference in the median is driven by the few very large deals in the PTP sample.

There seems to be little variation between the two groups when looking at the variables representing leverage (D/V, D/EBITDA, D/EV). This suggest that leverage choice in public companies is not an important trait for PE firms when selecting their investments. Interestingly, the average beta is 1.1 in the two groups. If the S&P 600 represented the whole market we would expect to find a beta of 1. However, the observed beta for the S&P 600 can be explained by the index´s bias towards small cap stocks, which tends to have more volatile returns (Jegadeesh and Titman 2001).

Overall, the descriptive statistics provide early indications of PE targeting small companies. This finding will be important for later analysis.

5.3 Variable Selection

5.3.1 Selected Variables

The objective of the study is to give a better understanding of the appropriate risk-adjusted benchmark for measuring the opportunity cost of investing in PE. Therefore, the aim of our variable selection is to maintain a complete representation of the systematic risk factors of public-to-private companies. The choice of potential explanatory variables is based on theory, previous studies and economic reasoning. All variables used in the empirical assessment are described in Table 4.

Table 4
Description Regression Variables Statistics

This table provides an overview of the variables included in the regression models. The variables are divided into dependent variables, independent variables and control variables. All accounting measures are denominated in USD.

Dependent variables:

Public-to-private dummy - dummy variable indicating a public equity taken private (1 if taken private, 0 otherwise).

Independent variables:

Beta - Beta is the estimated slope coefficient from a regression using the past 60 months of excess returns (requiring at least 36 valid returns).

EV/EBITDA - EBITDA multiple is calculated as the ratio of firm enterprise value to trailing 12-month earnings before interest, taxes, depreciation and amortization. The firm enterprise value is the sum of long term debt and the market value of equity less cash and marketable securities.

ME - market capitalization is the number of shares outstanding times the share price.

Sales - 12-month trailing revenue, less the cost of sales returns, allowances and discounts.

BE/ME - book-to-market equity ratio is calculated as the book value divided by the market capitalization. Book value is a firm´s common equity as of the latest available filing. The market cap for public-to-private companies are used by multiplying the number of shares outstanding by the price 4 weeks in advance of the announcement of the deal.

Profitability - measured as the ratio of 12-month trailing EBITDA to 12-month trailing sales.

D/V - total debt (long-term and short-term) as of the latest available filing to the sum of total debt and ME.

D/EBITDA - total debt to 12-month trailing earnings before interest, taxes, depreciation and amortization.

D/EV - total debt to firm enterprise value.

Control variables:

Year dummy - dummy variable that takes the value of 1 if the given year equals T=0 for the company.

The quantitative variables used for the purpose of this research includes well-known systematic risk factors. The included variables are beta, sales, market capitalisation (ME), EV/EBITDA, book-to-market ratio (BE/ME), debt to total value (D/V), EBITDA/Sales, debt to enterprise value (D/EV) and debt to EBITDA (D/EBITDA). We included beta, size proxied by market cap and value proxied by book-to-market ratio (BE/ME), as these variables represent the risk exposure used in the Fama and French three factor model discussed in Section 3.1.1. In addition, we included the EBITDA multiple as another proxy for value; the reason being that recent research has documented that EV/EBITDA is a more powerful variable than BE/ME for sourcing a value premium in stocks (Loughran, 2010; Stafford, 2017). An explanation may be that book value is generally a stale accounting measure, whereas enterprise value and EBITDA both incorporate the most recently available fundamental information. We also included another proxy for size, which is the size of a company.

There are two variables included for quality characteristics: profitability and leverage. To talk about a quality factor, we should have supplemented with additional quality characteristics. We tried to find other quality characteristics that would support the notion of whether PE funds were targeting quality companies, but the limited data availability for characteristics such as profit growth, re-investments, asset growth, and return on equity, entailed a limited quality factor. We therefore speak of a potential quality factor by looking at the statistical reliability of the quality characteristics, but not a quality factor per se. The quality characteristics have limited implications on benchmark adjustments, but are still valuable to include in a discussion on what company characteristics PE funds target. There are also has potential implications for the size premium, as Asness et al. (2015) found evidence that the size premium is significant, and stable through time, when controlling for quality/junk.

5.3.2 Assessment of Robustness

Before proceeding to the empirical results in Section 6.1, we consider potential issues that could affect our results and specify our preferred model.

First, we address the issue of the potential large influence of outliers in the sample. To address this concern, we examine the distribution of the variables included in the analysis. Numerous companies report extreme values for beta, EV/EBITDA, BE/ME, EBITDA/Sales and D/EBITDA. The presence of outliers could greatly affect the covariate pattern and mislead our interpretation. To address this issue we create winsorized variables. This is applied in the event of extreme values to reduce the effect of potentially spurious observations, which could give a skewed impression of the dataset. Winsorizing entails assigning extreme observations in the sample to a specific quartile. Instead of removing outliers, we adjust the variables by winsorizing. The outliers are winsorized at a 99% level, meaning that values below the 0.5% percentile are set to the 0.5% percentile, whereas the 0.5% highest values will be assigned to the 99.5% percentile. Winsorizing was applied to five variables: beta, EV/EBITDA, D/EBITDA, EBITDA/Sales and BE/ME. The variable selection was based upon examination of the existence, and extent, of values for each variable that could be considered outliers. For financial ratios outliers in the dataset are quite common; in particular for, multiples.

Second, variables with a severely skewed distribution were log-transformed to decrease the variability of data and make the data conform more closely to the normal distribution. It is recognised in the literature that data series of financial ratios are rarely normally distributed (Deakin 1976). In contrast to the linear probability model, the logit model is not based on the assumption of the normal distribution of errors. However, the transformation is done to further address the issue of outliers by reducing the skewness. The variables ME, Sales, BE/ME, EV/EBITDA, EBITDA/Sales are log-transformed.

Third, we examine the potential issue of multicollinearity. It is widely acknowledged within the bankruptcy and takeover prediction literature that the financial variables commonly used have the potential to exhibit high degrees of collinearity (Barnes, 1999). Multicollinearity refers to the phenomenon whereby one independent variable can be expressed as a linear function of two or more of the other independent variables (Stock and Watson, 2011). The primary concern is that high degrees of multicollinearity could cause unstable regression models and the standard errors of the coefficients could get wildly inflated (Greene, 1993). We address the issue of multicollinearity by applying two different procedures. The first procedure is the calculation of the correlation matrix. This allows us to evaluate the first order correlations between the independent variables. Correlations above 0.90 indicate substantial collinearity (Hair et al., 2013, p.196). The problem with this procedure is that multicollinearity may be caused by higher order correlations. Thus, the exclusion of variables only based on correlations could lead to an ineffective reduction of multicollinearity. The second procedure addresses this issue by calculating Variance Inflation Factors (VIF). VIF quantifies how much the variance is inflated (Stock and Watson, 2011). The variance of the coefficients is inflated when multicollinearity exists, implying that high values of VIF indicate a problem with multicollinearity. The general rule of thumb is that VIFs above 4 require further investigation, while VIFs exceeding 10 are signs of serious multicollinearity requiring correction (Hair et al., 2013)[18]. VIF are obtained by estimating an OLS regression model using the same dependent and independent variables as in the logistic regression model[19]. This is appropriate "because the concern is with the relationship among the independent variables, the functional form of the model for the dependent variable is irrelevant to the estimation of collinearity" (Menard 2002, p. 76).

Table 5 illustrates the correlation matrix for the independent variables considered in our empirical analysis. Examination of the table indicates that most correlations are moderate. However, the variables representing leverage are correlated to each other. The D/V variable is almost perfectly positively correlated with D/EV. This is not surprising as both have total firm debt as the numerator, and a firm value proxy as denominator. For the remaining variables, there seems to be no issue of high correlations.

[18] VIF of 4 and 10 is equivalent to a tolerance level of 0.25 and 0.10. The tolerance level is simply the inverse of VIF.
[19] Both correlation matrix and VIF are calculated by using the software package STATA.

Table 5
Correlation Matrix

The table present the correlation between the potential explanatory variables. Correlations lower than -0.8 or higher than 0.8 are shown in bold.

	Beta	ln(ME)	ln(Sales)	ln(BE/ME)	ln(EV/EBITDA)	ln(EBITDA/Sales)	D/V	D/EV	D/EBITDA
Beta	1.00								
ln(ME)	-0.03	1.00							
ln(Sales)	0.00	0.44	1.00						
ln(BE/ME)	0.06	-0.49	0.16	1.00					
ln(EV/EBITDA)	0.09	0.21	-0.22	-0.35	1.00				
ln(EBITDA/Sales)	-0.13	0.27	-0.42	-0.28	-0.31	1.00			
D/V	-0.02	-0.30	0.29	0.46	-0.18	-0.10	1.00		
D/EV	0.02	-0.31	0.26	0.48	-0.19	-0.11	**0.97**	1.00	
D/EBITDA	0.09	-0.14	0.10	0.20	0.46	-0.38	0.58	0.58	1.00

However, the examination of Table 2 in Appendix E suggests a more widespread problem. The mean Variance Inflation Factor in the fully specified model is 19.80, well above the critical level. Six variables in the table exhibit an extremely high Variance Inflation Factor. Including these variables in a regression could create multicollinearity, which could severely affect the estimated coefficients. It could cause the coefficients to switch signs, and lead us to wrong conclusions. To address the issues of multicollinearity, we exclude D/V as it correlates highly with D/EV and exhibits high VIF. Furthermore, ln(Sales) are discarded because of the high VIF. Finally, D/EBITDA is excluded, as variables that have similar numerators or denominators are generally the cause of multicollinearity problems. Removing these variables seems to eliminate the multicollinearity problems, as illustrated by the correlation matrix and VIF, shown in respectively, Table 1 and Table 2, respectively, in Appendix F. Running the model while excluding these variables seems to eliminate the issue of multicollinearity, with the highest VIF value being 1.41. To conclude, in our final regressions multicollinearity is not perceived as a problem.

The regression specification are as follows:

$$L = \ln\left(\frac{p}{1-p}\right) = a + b_1 Beta_{it} + b_2 \ln(ME)_{it} + b_3 \ln(\frac{BE}{ME})_{it} + b_4 \ln(\frac{EV}{EBITDA})_{it} + b_5 \ln(\frac{EBITDA}{Sales})_{it} + b_6(\frac{D}{EV})_{it} + \sum_{t=1997}^{2017} T_t Year_t$$

The model is specified with the public-to-private dummy as the dependent variable. We have included year dummy variables to control for aggregate time effects, and implicit control for unobserved heterogeneity[20].

[20] To avoid perfect collinearity we have omitted year dummy for 1997.

5.4 Limitations

We have identified several limitations for the model. In general, the secretive of the industry makes it difficult to capture all the systematic risk factors driving returns into a model. Even for public-to-private buyouts, historical data has proven difficult to find for many transactions. The model is limited by restricted access to basic financial data about PE buyouts, which has implication for the variable selection and the observations excluded due to missing information.

In the variable selection there is no control variable for sector (despite available sector data for the observations in the SDC database). We have an average of 17 observations per year, which entail that sectors allocation would be difficult to control for. The results would be little robust when controlling for the sector, due to few, or no observations, for a given sector over several years. The method is consistent with previous research (e.g. Stafford, 2017), which makes it simpler to compare the results. However, sectors should be expected to have systematic differences for financial multiples, and it could certainly improve the model to control for sector allocation.

Table 6
Sector Allocation Public Equities vs Private Equity

The table present the sector allocation in public markets and private equity, and the difference between the two. The table is adapted from Døskeland and Strömberg (2018, p. 76). The public market weights are based on the FTSE Global All-Cap Public Index as of December 2016. The private equity (buyout) weights are an average of the sector allocation over the period 2011 to 2016 using deal-level data.

Sector	Public market weights 16-Dec	CIQ PE buyout deals 2011-2016	PE-public diff
Consumer Discretionary	12%	19%	7%
Consumer Staples	10%	6%	-4%
Energy	7%	7%	0%
Financials	23%	8%	-15%
Healthcare	11%	9%	-2%
Industrials	14%	14%	0%
Information Technology	12%	17%	5%
Materials	5%	6%	1%
Real Estate	0%	10%	10%
Telecommunication Service:	3%	2%	-1%
Utilities	3%	4%	1%

In Table 6, Døskeland and Strömberg (2018) observe a different sector allocation to PE than public markets, implying that PE might be overrepresented in certain sectors. In practice, the commercially available trading products claiming to partially track private equity returns focus on sector weights. State Street offer a dynamic investing product called iGX Liquid Private Equity Index, which seek to track *"a portion of aggregate private equity performance by replicating private equity sector exposures in liquid public markets"*[21]. DSC Quantitative Group, in cooperation with Thomas Reuters, replicate PE return through predictive modelling, and takes it one step further by adding a modest amount of debt (around 25%) to more closely assimilate the higher debt ratios for private-equity portfolios[22]. The sector weights replication indexes place a greater emphasize on ongoing changes in the industry. Our method is more static as we are interested in the use of ex-post data to specify a risk-adjusted benchmark which needs to be set ex-ante. Bailey (1992) stated that one of the quality characteristics for a proper benchmark is that it should be specified in advance. The dynamic commercially available products are based on continuous input of – and adaption to – new data, which might be a more accurate way to replicate the returns for private equity if PE managers have fluctuating selection criteria. Although the dynamic indexes are not set in advance, they are investable and follow a specific strategy, and can thus be representative of the opportunity cost. The State Street private equity index is by a few LPs used as a benchmark, for example by the California State Teachers Retirement System and the Teachers Retirement System of the City of New York (Appelbaum and Batt, 2017).

The empirical analysis use only investable factors because a good benchmark should be investable. This leads us to exclude factors that may help explain the systematic risk factors in PE investments. Franzoni et al. (2012) and Ang et al. (2018) found significantly positive loading on the Pastor and Stambaugh liquidity factor. The empirical analysis does not include a liquidity risk factor because the cost of liquidity varies greatly by investor and over time. The implication of excluding a liquidity factor could be that the benchmark may overestimate alpha and underestimate the systematic risk. In addition to liquidity risk, PE investments exhibit commitment risk (Harris, Jenkinson og Kaplan 2014). Commitment risk is related to the uncertainty of cash flows and deviations from target allocations. The

[21] "State Street Embraces New Investment Paradigm, Launches Investable Indices". (State Street Corporation, 06.March.2018), http://newsroom.statestreet.com/press-release/corporate/state-street-embraces-new-investment-paradigm-launches-investable-indices (accessed 01.June.2018)
[22] "Thomas Reuters Private Equity Buyout Index Methodology". (DCS Quantitative Group, April. 2018), https://www.dscqg.com/private_equity_methodology.html

compensation for bearing illiquidity and commitment risk can be substantial (Ang et al., 2014). These considerations are not taken into account in our thesis.

6. Empirical Analysis and Results

In this section, we document the results from the empirical analysis and discuss the findings compared to earlier research. The objective of assessing underlying characteristics of companies selected by PE investors is to improve the understanding of the asset class' exposure to systematic risk.

We start by providing a brief overview of the findings for the full sample period (1997-2017) using the S&P 600 as the public market proxy. To see if the findings are statistically reliable over time, the dataset is then split into two sub-samples: from 1997 to 2007 (197 observations), and from 2008 to 2017 (179 observations). The results from using S&P 400 and S&P 500 as the public market proxy are compared to the main findings to control for potential risk specific characteristics of the S&P 600. The results are then discussed in-depth with respect to relevant findings from other studies to examine statistical reliability and consistency.

6.1 Empirical Results

6.1.1 Full Sample

Table 7 reports results from logistic regressions explaining which various lagged firm characteristics are associated with PE backed buyouts of public equity from 1997 to 2017. The regressions indicate that PE funds tend to select small profitable firms with conservative capital structures (relatively low leverage ratios), with these variables being highly statistical significant. Size (ME) and leverage (D/EV) is negatively associated with the event, whereas profitability (EBITDA/Sales) is positively associated with the event. Surprisingly, we find that market beta, and the value proxies; BE/ME and EV/EBITDA, are not reliable predictors of PE selection. The results are robust to the use of different regression models, as illustrated in Appendix G, see Table 1. The table reports results from an linear probability model, which yields similar results as the logit model.

The regression in specification 10 has a little predictive power indicated by the low pseudo R-squared (8.7%). Comparing the full specified model to the model with only size as the explanatory variable (specification 3), we find that size as proxied by market capitalization seems to be the single most important variable predicting PE asset selection. The variable is highly negatively significant when regressed on the public-to-private dummy. Further evidence of this is given by the relatively low increase in predictive power when including other explanatory variables in addition to size. This suggests that the other explanatory variables do not help much to discriminate the two groups.

Table 7
Regressions Explaining Public Equities taken Private (1997-2017)

This table reports the results of regressions of a binary variable indicating a public equity was taken private on various lagged firm characteristics. The regressions are logistic regressions. The sample consist of the identified PE-backed companies and S&P 600 constituents. The number of observations represents both the PE-funded and the controls. The time period is 1997 to 2017. All specifications include year fixed effects. z-statistics are reported in parentheses. Significance levels 10 %, 5 %, 1 % are denoted by asterisks ***, ** and *, respectively.

Logistic Regression (1997-2017)

Independent Variables	1	2	3	4	5	6	7	8	9	10
Beta	-0.0867									-0.112
	(-0.77)									(-1.03)
ln(Sales)		-0.562***								
		(-6.44)								
ln(ME)			-0.541***							-0.739***
			(-5.19)							(-5.66)
ln(BE/ME)				0.135						0.0760
				(1.28)						(0.48)
ln(EV/EBITDA)					-0.00369					0.295*
					(-0.03)					(2.34)
ln(EBITDA/Sales)						0.108				0.417***
						(1.46)				(4.39)
D/V							-0.559			
							(-1.66)			
D/EBITDA								-0.0359		
								(-1.63)		
D/EV									-0.505	-1.094**
									(-1.60)	(-3.03)
Observations	6851	6851	6851	6851	6851	6851	6851	6851	6851	6851
Pseudo R-squared	0.047	0.079	0.072	0.048	0.047	0.047	0.048	0.048	0.048	0.087
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

6.1.2 Sub Samples

To examine the statistical reliability over time, the samples are split into two time-periods. The results for the two sub-samples of the periods from 1997 to 2007 (197 observations) and from 2008 to 2017 (179 observations) are shown in Table 8.

We find that the size and the profitability characteristics remain reliable predictors for PE selection over time. The statistical reliability of leverage and EV/EBITDA (value proxy) changes over time, adding further skepticism towards a value premium for private equity. The leverage coefficient remain negative for both periods, although the findings are not statistically significant in the first period (1997-2007). The concern is lessened by more statistically reliable findings in the recent period (2008-2017). Beta and BE/ME (value proxy) remain unreliable predictors for PE selection. The predictive power of the model is higher in the first subsample, which may suggest that PE look for other characteristics in the more recent period than earlier when choosing their targets. Overall, the findings are quite robust over time, and qualitatively similar to the full sample. This suggests that the company characteristics attracting PE firms are stable over time. This finding will be useful when constructing a benchmark.

Table 8

Sub-Sample Logistic Regressions Explaining Public Equities taken Private

This table reports the results of logistic regressions of a binary variable indicating a public equity was taken private on various lagged firm characteristics. Panel A reports results for the period 1997 to 2007. Panel B reports results from the period 2008 to 2017. The sample consist of the identified PE-backed companies and S&P 600 constituents. The number of observations represents both the PE-funded and the controls. All specifications include year fixed effects. *z*-statistics are reported in parentheses. Significance levels 10 %, 5 %, 1 % are denoted by asterisks ***, ** and *, respectively.

Panel A: Logistic Regression (1997-2007)

Independent Variables	1	2	3	4	5	6	7	8	9	10
Beta	-0.0890									-0.0889
	(-0.59)									(-0.60)
ln(Sales)		-0.478***								
		(-3.81)								
ln(ME)			-0.692***							-0.723***
			(-4.95)							(-3.65)
ln(BE/ME)				0.656***						0.443
				(4.20)						(1.56)
ln(EV/EBITDA)					-0.457*					0.0625
					(-2.55)					(0.30)
ln(EBITDA/Sales)						0.00448				0.392**
						(0.05)				(2.73)
D/V							0.434			
							(1.00)			
D/EBITDA								0.000492		
								(0.02)		
D/EV									0.395	-1.015
									(0.98)	(-1.78)
Observations	3075	3075	3075	3075	3075	3075	3075	3075	3075	3075
Pseudo R-squared	0.079	0.103	0.124	0.098	0.085	0.079	0.080	0.079	0.080	0.136
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Logistic Regression (2008-2017)

Independent Variables	1	2	3	4	5	6	7	8	9	10
Beta	0.00194									0.0946
	(0.01)									(0.56)
ln(Sales)		-0.840***								
		(-6.46)								
ln(ME)			-0.682***							-1.035***
			(-4.61)							(-5.69)
ln(BE/ME)				-0.177						-0.193
				(-1.16)						(-1.05)
ln(EV/EBITDA)					0.132					0.438*
					(0.90)					(2.31)
ln(EBITDA/Sales)						0.240*				0.627***
						(2.05)				(4.49)
D/V							-1.535*			
							(-2.48)			
D/EBITDA								-0.0776		
								(-1.81)		
D/EV									-1.289*	-1.488**
									(-2.24)	(-2.89)
Observations	3395	3395	3395	3395	3395	3395	3395	3395	3395	3395
Pseudo R-squared	0.015	0.083	0.051	0.016	0.015	0.018	0.022	0.020	0.021	0.090
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

6.2 Comparison with Relevant Literature

In this section, we will discuss how our findings compare to the related literature focusing on the asset selection by PE. The logit model has a limited explanatory power for PE selection (Section 6.1.1), and the data sample and methodology impose certain weaknesses (Section 4.4) and limitations (Section 5.4). Consequently, the comparison of the findings is a key component of the empirical analysis, to further assess the reliability of our results. The variables will be presented and discussed in individual paragraphs. The main focus will be on the findings of Stafford (2017). Table 9 illustrates our findings in relation to the results from Stafford (2017).

Table 9
Empirical Results Compared to Stafford (2017)

The table present the empirical results from our study and Stafford (2017). Although Stafford apply the findings for a different purpose, the comparison is relevant to consider the robustness of our findings. Stafford's sample of 711 deals is before exclusion, unlike our sample of 355 deals which is after the inclusion criteria are applied.

	Empirical Results	Stafford (2017)
Beta	insignificant (-)	insignificant (-)
Size (ME)	(-)	(-)
Value (EV/EBITDA)	insignificant (+)*	(-)
Value (BE/ME)	insignificant (+)	(+)
Profitability (EBITDA/Sales)	(+)	(-)
Leverage (S: D/V; Our study: D/EV)	(+)	insignificant (-)
ISS	N/A	(-)
Sample size	355	711
Period	1997-2017 (21 years)	1983-2014 (31 years)

*Significant at 10% level

The negative coefficient on the size proxy “Market Capitalization” suggests that the targeted firms are smaller than the average public market company. Although previous research supports the findings of PE backed buyouts being weighted towards relatively small size companies (Stafford, 2017), the results are not directly comparable given our market proxy being biased towards small-cap companies. Despite several large acquisitions in the mid-2000s, the results are hardly surprising; in the descriptive analysis we find that the inflation-adjusted medians for the period were $912 million for the public sample compared to $519 million for the PTP sample. The negative coefficient on sales (another common proxy for size) further strengthen the findings that the selected firms are relatively small.

The positive coefficient on profitability (EBITDA/Sales) suggest that PE funds target highly profitable companies. The findings are inconsistent with Stafford (2017) who find that selected companies are not highly profitable. However, Stafford applies an inclusion criterion for the regression of firms having a minimum EBITDA of $1 million, while we exclude negative EBITDA values and apply winsorization to reduce the effect of outliers (see Section 4.1 for more information). Although the results are not reported, Stafford states that the coefficient on profitability is positive without the condition of EBITDA above $1 million (only excluding negative values), which would be more consistent with our findings.

The positive coefficient on the value proxy EV/EBITDA, although weakly statistically reliable, suggest that PE funds target growth firms. Recent research has documented that EV/EBITDA is a more powerful variable than BE/ME for sourcing a value premium in stocks (Loughran, 2010; Stafford, 2017). The reason could be that book value is generally a stale accounting measure, whereas enterprise value and EBITDA both incorporate the most recently available fundamental information. As with earlier research (Stafford, 2017), the value proxy BE/ME is not significant when both value proxies are included in the same specification. However, BE/ME is still not statistically significant when we exclude EV/EBITDA, while the positive coefficient for EV/EBITDA is weakly significant when excluding BE/ME (results not reported).

The finding are surprising, as we would expect PE investors to target value firms based on findings in earlier research (e.g. Phalippou, 2014; Stafford, 2017; Døskeland and Strömberg, 2018). Phalippou (2014) used the implied equity value to book value of 537 companies at transaction announcement, and conclude that the PE portfolio companies are value companies. Døskeland and Strömberg (2018) found a positive loading on value by estimating risk loadings for publicly traded PE funds. However, L´Her et al. (2016) examine public-to-private and private-to-private transactions and found that PE is value neutral, which is more consistent with our results. It should be noted that we use the S&P indexes representing distinct market segment as public market proxies, while Stafford (2017) seem to rely on a more diverse public market proxy to run the regression[23]. If the S&P indexes have any inherent traits besides size, our results could be affected. Thus, we suspect our results might

[23] The study presented in Stafford (2017) does not specify the structure of the public market proxy. We do suspect that the sample of publicly traded firms is considerably higher as the objective of the study is different. As we are interested in potential risk-adjustment to an investable index, it makes sense to use the composite companies of these indexes as market proxy . While Stafford (2017) is interested in replicating.

have a relation to the choice of public market proxy, which we will discuss in Section 6.3. Furthermore, the EV/EBITDA coefficient changes to negative when applying Sales (instead of ME) as a proxy for size. Overall, our finding of PE targeting growth companies is not statistically reliable, and we conclude that there is not enough support for any specific weighting on the value premium presented by Fama and French (1992).

The negative coefficient on leverage suggest that selected firms tend to have low leverage ratios. The results are statistically significant whether D/V, D/EBITDA or D/EV is used in the regression as the debt metric (results not reported). The findings are inconsistent with Stafford (2017) and Axelson et al. (2013). Stafford (2017) found no evidence of leverage being a reliable predictor for target selection, while Axelson et al. (2013) found no systematic relation between the target firm's leverage pre-transaction and leverage choice by the PE post-transaction. Instead, leverage is seemingly determined by time-series effects in credit markets conditions. However, we find that leverage is a reliable predictor of whether a company is acquired by a PE sponsor. It should be noted that Stafford (2017), besides looking at a different time period, regress the model based on another variable; Composite share issuance (ISS). The composite share issuance variable measures the amount of equity the firm issues (or retires) in exchange for cash or services (Daniel and Titman, 2006). As the D/V variable is a product of debt and equity, there might be some correlation between the D/V and the composite share issuance - which is related to equity value.

Beta is not a reliable predictor for PE selection in our model. It should be noted that in the descriptive analysis the average beta for our public sample slightly deviate from one. By definition, a public listed company has an average beta of one. The market proxy should, therefore, have a beta approximating one. The deviation mainly stems from values above one over the period, which can be explained by the S&P 600 index's bias towards small capitalization stocks, which tends to have more volatile returns (Jegadeesh and Titman 2001). This could affect our results as the beta of the PE selected companies is not compared against a beta of one, but a slightly higher value. However, the equity beta (levered beta) could be affected by a presumably more leveraged capital structure post-transaction, the implications of which will be discussed in detail in Section 7.1.

Stafford (2017) studied an earlier and longer time-period with more observations, examining public-to-private buyout transactions in the U.S. back to 1983. As mentioned earlier, we wanted to focus on a more recent time-period, effectively excluding two historical

PE-periods; the PE-boom occurring in the 1980s focused on highly leveraged capital structures, and the period after the crash in the U.S. junk bond market in the early 1990s where few public-to-private buyouts were completed. We do not have much support to claim any significant impact from using a slightly different time-period. Stafford (2017) also split the dataset into two period sub-samples, where the findings remain rather robust (only statistically reliable changes are for the BE/ME variable). Since the finding in Stafford (2017) and our study are somewhat inconsistent, but the respective predictors for PE selection in each study show persistency for the statistical reliability over time, we can conclude that the change for the data period does not suggest any changes in the predictors. Instead, the inconsistency seems to stem from different inclusions criteria and variations in variable selection.

6.3 Sensitivity to the Choice of Public Market Proxy

The previous discussion use the investable index S&P 600 as the public market proxy. In the following, we will assess the sensitivity to the choice of public market proxy by comparing the results to the use of investable indexes S&P 500 and S&P 400 as market proxy. The examination is relevant to consider if there are any inherent traits with the S&P 600, beside size, which affect the results in the model.

Table 1 in Appendix H reports the results of regressions of a binary variable indicating a public equity was taken private on various lagged firm characteristics with S&P 500 as the public market index. Panel A reports results from logistic regressions. Panel B reports results from ordinary least squares (OLS) regressions. The negative significant coefficient on size is no surprise as S&P 500 is a large cap index. The coefficient on profitability is positive and significant, consistent with our findings that PE targets firms with high profitability. Surprisingly, the coefficient on value proxied by EV/EBITDA is positive and highly significant. This suggest that PE tend to select growth firms, which is inconsistent with what previous research has found. The variable was weakly significant when using the S&P 600 as the market proxy, thus it increases our suspicion that PE is negatively exposed to the value factor. The variable representing leverage is negative, and highly significant. The model has a much more predictive power than the model presented in Section 6.1. However, the difference is driven by the size variable.

Table 2 in Appendix H reports the results of regressions of a binary variable indicating a public equity was taken private on various lagged firm characteristics with S&P 400 as the public market index. Panel A reports results from logistic regressions. Panel B reports results from ordinary least squares (OLS) regressions. The results is similar to the regression using S&P 500 as the market sample.

Overall, it seems that our findings are robust to the choice of public market index. It strengthens our evidence that PE tend to target small profitable firms with low leverage. In addition it seems that PE tend to choose growth companies represented by high EBITDA multiples. However, this effect can be driven by the different sector exposure between PE and public markets as discussed in Section 5.4.

7. Assessment of the Implications for Benchmark

The findings in the previous chapter have implications for the appropriate index, which can be used in a PME calculation for benchmarking of private equity returns. The empirical results suggest that PE funds select relatively small firms with low leverage and high profitability. The implication is that the asset class is tilted towards the size factor and to a certain degree quality characteristic. Surprisingly, we did not find a higher exposure towards the value factor. Size and leverage are the key systematic risk components we control for when comparing buyout fund returns and public market returns.

The results indicate that size is the strongest predictor of whether a public company is taken private. The S&P 600 index was favoured in Section 5.2 based on its constituents being biased towards small-cap firms, which was though to give a better assimilation to the type of companies selected and included in the private equity investment universe. When using the S&P 600 as the market proxy, the results still suggest that PE funds select significantly smaller companies. Consequently, the S&P 600 might be underexposed to the size risk premium when compared to the public-to-private companies - even further so if we consider the viewability of the PTP sample as a proxy for PE market with respect to size. Phalippou (2014) studied the entire buyout market from Capital IQ database. The database from Capital IQ is considered the most comprehensive publicly available data on these type of transactions (Strömberg, 2007). Phalippou (2014) found that, out of the 5136 buyout transactions listed in the dataset, 95% of the targets have a listed enterprise value below $1.08 billion. In comparison, for the PTP sample 60% of the companies had an enterprise value below $1.08 billion when measured in 2017 dollars pre-transaction (the percentage would have been even lower if measured by transaction price due to the acquisition premium). The implication is that the PTP sample overestimate the size of PE deals, and if anything, the public index should be smaller rather than larger to compensate for the predicament and accurately match for size.

While the S&P 600 is larger than optimal, further replicating the size characteristic might challenge the requirement from Bailey's (1992) framework of the benchmark being investable. Phalippou (2014) used the DFA Micro-Cap (ticker: DFSCX) to benchmark private equity returns based on the assumption that 95% of all leveraged buyouts investments fall below a $1.08 billion threshold. The DFA Micro-Cap mutual fund's objective is to invest in small- and micro-caps, without leverage, passively and at low cost. The mutual fund had by

March 2018 $6.3 billion under management[24]. It is not clear how sensitive the DFA Micro-Cap is to capital under management. However, it is likely that the returns could suffer if only a few billion dollars moved from PE to the mutual fund. The fund might become too large to efficiently move in and out of positions. Døskeland and Strömberg (2018) estimate the total global investable market for PE funds to be $2 trillion (not accounting for dry powder of $1.7 trillion in December 2017). For the benchmark to be investable, we only require it to be sufficiently large for a reasonable number of LPs to move their investment over to the benchmark over time without affecting the asset pricing. Although, for the scope of our study, the adjusted index is only meant to meet the criteria as an investable benchmark for allocation to U.S. buyout funds. We believe that S&P 600 would function as an investable benchmark for most LPs. The S&P 600 has a total market cap of $815 billion as of April 2018[25], and it is tracked by, for example, Vanguard's S&P 600 ETF - making it easily investable for investors at low cost (0.15% fees apply[26]). A larger small cap index is the CRSP US small cap index, which is made easily investable through Vanguard's Small-Cap ETF (0.05% fees apply). However, the constitution companies are significantly larger with a median market cap of $4.1 billion[27], compared to $1.2 billion for the S&P 600[28]. The S&P 600 appear to be the best fit with respect to size and the requirement of the benchmark being investable.

From the results we find that market beta is not a reliable predictor for PE selection. The empirical studies on KS-PME implicitly assume a leveraged beta of 1 (Kaplan and Schoar, 2004), which would be consistent with our findings if the capital structure remained unchanged in the buyouts (we use pre-transaction financials). From the results we find that the negative coefficient on leverage suggest that the target firms for PE funds have relatively low leverage. The pre-transaction leverage ratio has limited information by itself in a risk-adjustment. Axelson et al. (2013) found that there is no relation between pre-transaction leverage, and post-transaction leverage ratio. Instead, they suggest that the leverage ratio is determined by aggregate credit market conditions. Axelson et al. (2013, p. 2337) examined 366 U.S. public-to-private transactions between 1980 and 2008, and found that the amount of debt used increased the average D/EV to around 70%. They also found that public comparable had an average D/EV of 30%. In our study we look directly at the D/EV pre-transaction for

[24] Reported holdings as of March 31. 2018: $ 6,339,237,436.
[25] https://us.spindices.com/indices/equity/sp-600
[26] https://personal.vanguard.com/us/funds/snapshot?FundId=3345&FundIntExt=INT&funds_disable_redirect=true#tab=3
[27] http://www.crsp.com/products/investment-products/crsp-us-small-cap-index
[28] https://us.spindices.com/indices/equity/sp-600

the targets, and find an average D/EV of 24%, inferring an even greater increase in the leverage. The findings indicate an increase in leverage of 2.3-3x. Following the theorem of Modigliani and Miller (1958), such an increase in leverage would greatly increase the market beta.

For PE, increased availability of debt financing lead to higher competition, resulting in higher transaction prices, and lower returns. On the other hand, Axelson et al. (2013) found no apparent relationship between valuation, leverage, and credit market conditions for public companies. The credit market conditions are indicated as a predictor for the leverage ratio in private equity investments, but not for public companies. The implications are that a highly leveraged portfolio of public stocks with a fixed leverage ratio might not be correlated with PE returns if the underlying drivers for leverage in public and private companies are different. Research also indicate that PE investors (who have extensive experience with financial engineering) are better able to manage distress risk than comparable non-buyout companies (Tykvová and Borell 2011). GPs apparent ability to manage distress risk at a higher level than public comparable means that higher leverage might not just be a passive component, as there are some active components at display. Furthermore, the leverage added on company level is not directly comparable to leverage at portfolio level. At the portfolio level, the leverage will not manufacture the tax effects and costs of financial distress that increased leverage at the firm-level may produce (Stafford, 2017). Overall, the empirical reasoning calls for a more moderate leverage to the risk-adjusted index than implied by the changes in the capital structure for public-to-private buyouts. The moderate portfolio leverage, which can be added through a brokerage margin account, will alter the risk and return properties of the underlying equity for the index constituents.

We determine the appropriate risk-adjusted index to be a moderately levered size-adjusted index. The index can be used in a PME calculation representing the opportunity cost of investing in PE. As emphasized earlier, academic research has been widely based upon S&P 500 for measuring performance with KS-PME, including Jenkinson et al. (2015), Brown et al. (2015), Robinson and Sensoy (2016). In addition, S&P 500 is widely used in practice and Bain's annual Global Private Equity Report[29] base its PME calculations on S&P 500 for the U.S. market. L'Her et al. (2016) calculate the PME with the use of different indexes, with cash

[29] Bain & Company's Global Private Equity Report 2018

flow data from the Burgiss dataset. The PME for the value-weighted average[30] from 1986 to 2008 using the S&P 500 was 1.17 (EW 1.22), while it was 1.04 (EW 1.16) when using the S&P 600 (L'Her, 2016, p. 26). Furthermore, they adjust the S&P 600 by attempting to mirror the average leverage and get a value-weighted PME of 0.98 (EW 1.08) when using the size- and leverage adjusted index. The results suggests that PE outperforms public equities when the S&P 500 is used as the benchmarking discounting PE cash flows. When the benchmarked is changed to a levered size index, PE underperforms. Based on our empirical findings, a levered S&P 600 index would better represent the opportunity cost of investing in private equity than the S&P 500. If LPs use the S&P 500 index in PME calculations they may underestimate the systematic risk, and as a result overestimate alpha. The implication being that when evaluating PE performance, one should carefully consider what the opportunity cost of the investment is, and if there are certain characteristics leading to systematic differences in risk between the two alternatives. We would also like to emphasize that it would be difficult for an LP to risk-adjust their PE allocation based on general characteristics of the asset class due to individual differences between funds and their investment strategy. It could, therefore, be useful to have several benchmarks to evaluate PE returns. We do believe that a risk-adjusted benchmark, which can better capture the opportunity cost, should be one of them.

[30] The value-weighted average is based on the inflation-adjusted amount of invested capital in each vintage. Since capital deployed varies significantly between each year the value-weighted PME more accurately reflects the aggregate returns of LPs.

8. Conclusion and Future Research

The purpose of this thesis was to identify the systematic risks of underlying companies in private equity funds in order to inform an appropriate risk-adjusted benchmark.

By examining a comprehensive dataset comprised of public-to-private transactions and public companies, this study makes important contributions to the litterature on evaluation of private equity perfomance. First, the assessment of the underlying characteristics of companies targeted by buyout funds, contributes to a better understanding of the systematic risk factors inherent in private equity. Despite the increased importance of the asset class, there is a persisting ambiguity in regard to PE performance relative to public equities, and the drivers for the differences in perfomance. Our study adds to this discussion by suggesting the appropriate index to be used in a PME calculations. This is important for understanding the performance of PE against public equities, which is critical for asset allocation.

The study uses a comprehensive dataset comprised of both public companies and public companies taken private by a PE sponsor over the period from 1997 to 2017 in the U.S. We study a sample of 355 public-to-private deals, recognizing that the sample might be are not completely representative of the full sample. To get a sense of the type of companies PE invest into, we compare the firm characteristics of PE selected companies to companies listed on S&P 500, S&P 400 and S&P 600.

Using S&P 600 as the public market proxy, we find that PE investors tend to select relatively small firms with low leverage and high profitability. Surprisingly, we find that value proxied by BE/ME or EV/EBITDA are not reliable predictors of PE selection. The results are robust to the use of different regression models and the use of different public market proxies. We examine the statistical reliability of our results by splitting the sample into two time-periods: (1) 1997 to 2007 and (2) 2008 to 2017. We find that the results are quite robust over time, and qualitatively similar to the full sample. This suggests that the company characteristics attracting PE firms are stable over time.

The findings from our empirical analysis have implications for benchmarking private equity returns. We determine the appropriate risk-adjusted index to be a moderately levered size-adjusted index. The index can be used in a PME calculation representing the opportunity cost of investing in PE. As emphasized earlier, academic research has been widely based upon S&P 500 for measuring performance with KS-PME, including Jenkinson et al. (2015), Brown et al. (2015), Robinson and Sensoy (2016). Based on our empirical findings, a levered S&P 600 index would better represent the opportunity cost of investing in private equity than the S&P 500. If LPs use the S&P 500 index in PME calculations they may underestimate the systematic risk, and as a result overestimate alpha. The implication being that when evaluating PE performance, one should carefully consider what the opportunity cost of the investment is, and if there are certain characteristics leading to systematic differences in risk between the two alternatives. We would also like to emphasize that it would be difficult for an LP to risk-adjust their PE allocation based on general characteristics of the asset class due to individual differences between funds and their investment strategy. It could, therefore, be useful to have several benchmarks to evaluate PE returns. We do believe that a risk-adjusted benchmark, which can better capture the opportunity cost, should be one of them.

As the findings in this study suggests, PE firms target companies with certain characteristics. A relevant question for future research is whether PE returns could be replicated in public markets by mimicking the asset selection of PE, and if this could be used for benchmarking. Stafford (2017) argues that a passive portfolio based on predicitive characteristics could mimick the returns to private equity. The argument being that PE returns are spanned by public equity risk factors. However, he does not use the replicating portfolio for benchmarking purposes. Such a replicating portfolio could be used to form a more dynamic benchmark to assess the performance of private equity.

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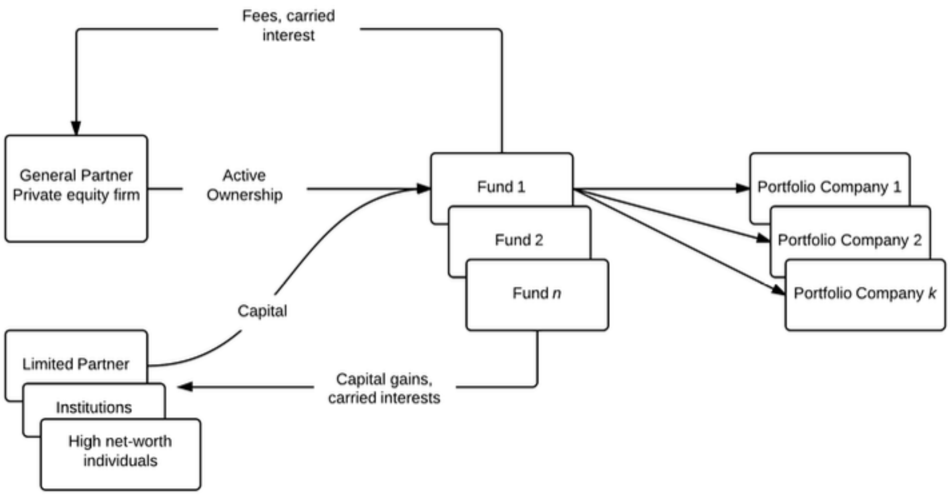
Appendix

Appendix A

Figure 1
Private Equity Model

PE firms raise capital from institutional investors such as insurance companies, pension funds, endowments, sovereign wealth funds, as well as high net worth individuals. Investors in these funds are known as limited partners (LPs). The general partner (GP), is responsible for sourcing, making and exiting the investments on behalf of the fund. During the ownership period, the PE firm tries to increase the value of the portfolio company through active ownership. The GP is compensated by charging management fees and performance fees. The figure below is from Gilligan and Wright (2010).



Appendix B

Table 1
Well-Known Systematic Risk Factors

The table describe systematic risk factors found in the literature and how they are commonly captured.

Systematic Risk Factors	Description	Commonly Captured by
Value	Captures excess to stocks that have low prices relative to their fundamental value	BE/ME, EV/EBITDA
Size	Captures excess returns of smaller firms relative to their larger counterparts	Market capitalization, sales
Momentum	Reflects excess returns to stocks with stronger past performance	Relative returns (3-month, 6-month, 12-month)
Quality	Captures excess returns to stocks that are characterized by low debt, stable earnings growth, and other "quality" metrics	ROE, earnings stability, dividend growth stability, strength of balance sheet, financial leverage, accounting policies, strength of management, accruals, cash flows

Appendix C

Table 1
Search Criteria SDC Database

The table describe the filters applied in the SDC database, and the resulting number of transactions.

Search Criteria SDC Database (1997-2017)

Step	Request	Operator	Description	Number of Transactions
1	Database	Include	Domestic Mergers, 1979-Present	-
2	Date Announced	Between	01.01.1997 to 31.12.2017	-
3	LBO	Include	All Leveraged Buyouts	10 399
4	Aquiror Firm Type	Include	Financial Buyer	9 121
5	Shares Owned	Between	Percent of Shares Owned after Transaction	7 104
6	Deal Status	Include	Completed	7 104
7	Going Private	Include	All Going Privates	551
8	Target Primary SIC	Exclude	6000-6799	515

Appendix D

Figure 1
Sample Size S&P 500

The table show the number of observations of the S&P 500 sample over the period 1997 to 2017.

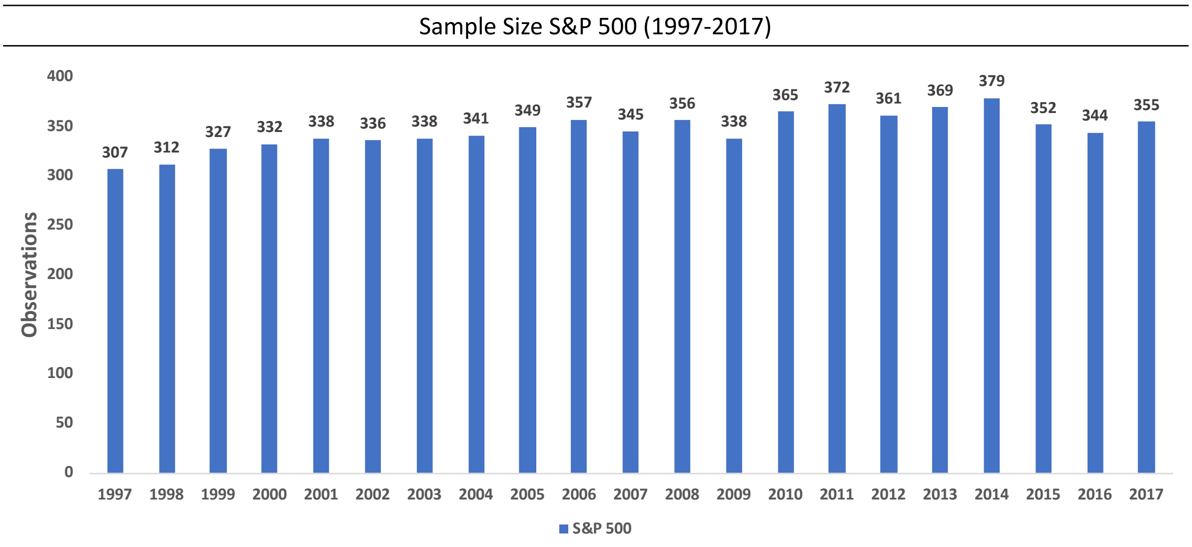
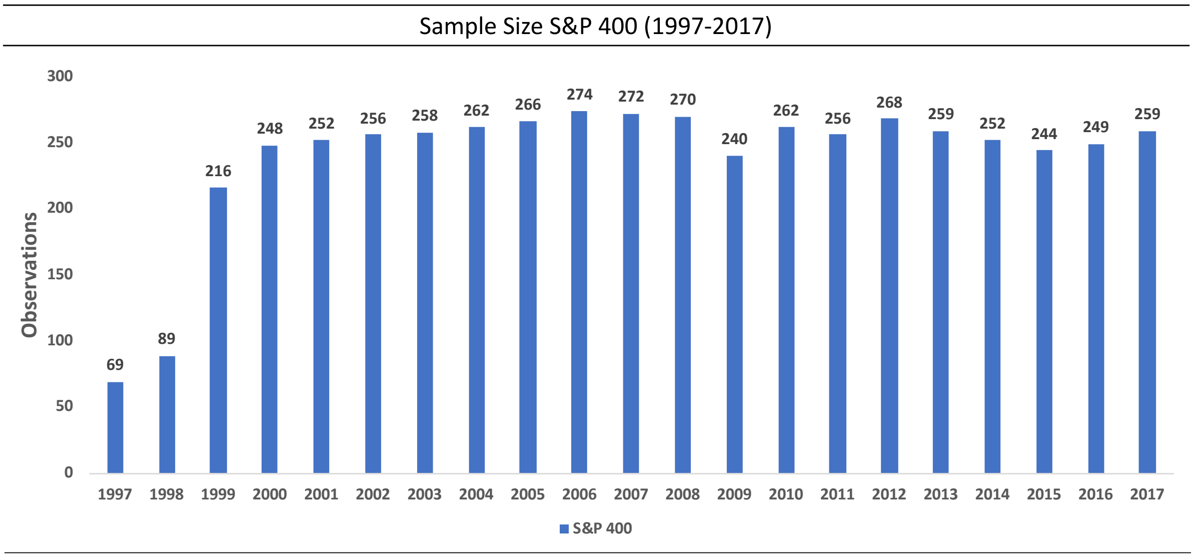


Figure 2
Sample Size S&P 400

The table show the number of observations of the S&P 400 sample over the period 1997 to 2017.



Appendix E

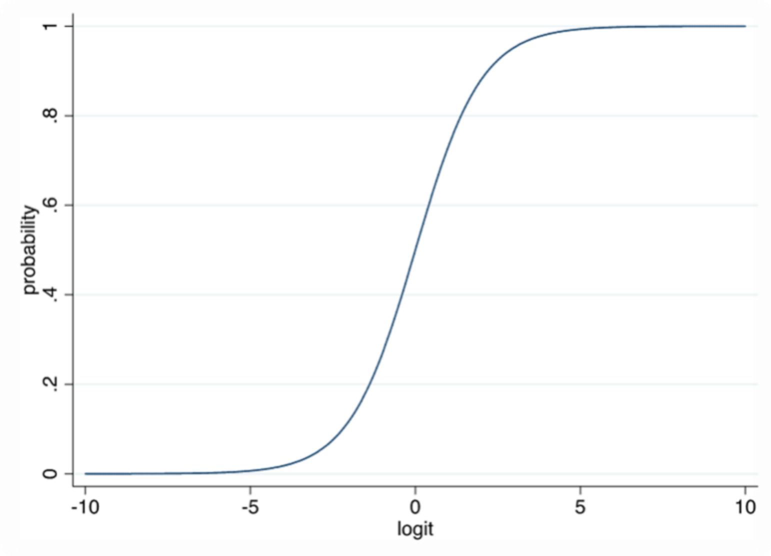
Multivariate Logistic Regression Model

Logit regression are nonlinear regression models specifically designed for a binary dependent variable[31]. The model combines multiple variables into one model to estimate a prediction model. It models the relationship between the probability of an event $\Pr(Y_i=1|X_i)$ and the independent variables.

The logistic model overcomes many of the limitations of the Linear Probability model (LPM)[32]. It overcomes the limitations by condensing the probability to a value between zero and one[33]. The main disadvantage with the LPM is that it could give predicted probabilities above 1 or below 0. The LPM stipulates a linear relationship between the dependent variable and the independent variables, whereas the logit model suggest a non-linear relationship between the PTP likelihood and the explanatory variables. The adoption of a nonlinear formulation forces the predicted values to be between 0 and 1 (Stock & Watson, 2011). The S-shaped curve in the figure below is portraying this relationship.

[31] Binary dependent variable takes on only two values: zero and one.
[32] LPM is equivalent to OLS with a discrete dependent variable.

[33] The linear probability model could give predicted probability above 1 or below 0 (Stock & Watson, 2011).



The logistic regression model use odds ratio in order to eliminate the upper limit of the dependent variable (Tufte, 2000). The odds ratio is defined as:

$$Odds = \frac{p}{(1-p)}$$

The odds ratio measure the ratio of the probability of Y = 1 relative to the likelihood of Y = 0. The ratio eliminate the upper limit of one. The natural log of odds ratio will remove the lower limit of the dependent variable. It gives the logistic regression output[34], L:

$$L = \ln\left(\frac{p}{1-p}\right) = b_0 + b_1X_1 + \ldots + b_nX_n$$

$$where\ p_i = \Pr(Y_i = 1)$$

$$p_i = \Pr(Y_i = 1|\boldsymbol{X_i}) = F(b_0 + b_1X_1 \ldots + b_nX_n) = \frac{1}{1 + e^{-(b_0 + b_1X_1 \ldots + b_nX_n)}}, \qquad i = 1, \ldots, k$$

Where observations are indexed with subscription i, k is the number of observations; and $b_0, b_1, .., b_n$ are regression coefficients for n explanatory variables. The logit model are nonlinear in the coefficients, and the parameters are estimated using the maximum likelihood estimation (MLE). The MLE are the values of the coefficients that maximise the likelihood function. MLE´s are the values of $b_0, b_1, \ldots, b_n$ most likely to have produced the data. The estimated regression coefficients are interpreted as the change in log-odds associated with a one unit change in the independent variable, ceteris paribus. Exponentiating the coefficient gives the odd ratio associated with a one unit change in the independent variable.

[34] Peng, Lee & Ingersoll, 2002

Appendix F

Table 1
Correlation Matrix

The table presents the correlation between the independent variables applied in the logit model. Correlations lower than -0.8 or higher than 0.8 are shown in bold.

	Beta	ln(ME)	ln(BE/ME)	ln(EV/EBITDA)	ln(EBITDA/Sales)	D/EV
Beta	1.00					
ln(ME)	-0.03	1.00				
ln(BE/ME)	0.06	-0.49	1.00			
ln(EV/EBITDA)	0.09	0.21	-0.35	1.00		
ln(EBITDA/Sales)	-0.13	0.27	-0.28	-0.31	1.00	
D/EV	0.02	-0.31	0.48	-0.19	-0.11	1.00

Table 2
VIF Test for Multicollinearity

The table shows a Variance Inflation Factor test for multicollinearity. The test quantifies how much of the variance is inflated due to a correlation between two or more variables. VIFs above 4 requires further investigation, while VIFs exceeding 10 are signs of serious multicollinearity requiring correction. In the table below VIF and 1/VIF are presented.

Test	1	2	3	4
Beta	1.02	1.02	1.05	1.05
	(0.98)	(0.98)	(0.96)	(0.95)
ln(ME)	1.38	1.38	15.05	30.53
	(0.72)	(0.72)	(0.07)	(0.03)
ln(Sales)			17.64	37.49
			(0.06)	(0.03)
ln(BE/ME)	1.86	1.87	1.87	1.88
	(0.54)	(0.53)	(0.53)	(0.53)
ln(EV/EBITDA)	1.46	2.52	8.83	16.17
	(0.68)	(0.40)	(0.11)	(0.06)
ln(EBITDA/Sales)	1.43	1.47	12.76	26.18
	(0.70)	(0.68)	(0.08)	(0.04)
D/V				37.65
				(0.03)
D/EV	1.31	2.69	4.63	23.97
	(0.76)	(0.37)	(0.22)	(0.04)
D/EBITDA		3.29	3.29	3.29
		(0.30)	(0.30)	(0.30)
Mean VIF	**1.41**	**2.04**	**8.14**	**19.8**

Appendix G

Table 1

Regressions Explaining Public Equities taken Private (1997-2017)

This table reports the results of regressions of a binary variable indicating a public equity was taken private on various lagged firm characteristics. The regressions are OLS regressions. The sample consist of the identified PE-backed companies and S&P 600 constituents. The number of observations represents both the PE-funded and the controls. The time period is 1997 to 2017. All specifications include year fixed effects. The OLS regression standard errors are clustered by firm with t-statistics reported in parentheses. Significance levels 10 %, 5 %, 1 % are denoted by asterisks ***, ** and *, respectively.

OLS Regression (1997-2017)

Indepedent Variables	1	2	3	4	5	6	7	8	9	10
Beta	-0.416									-0.779
	(-0.78)									(-1.44)
ln(Sales)		-2.691***								
		(-6.24)								
ln(ME)			-2.940***							-4.008***
			(-4.68)							(-5.14)
ln(BE/ME)				0.638						0.216
				(1.30)						(0.28)
ln(EV/EBITDA)					-0.0171					1.278*
					(-0.03)					(2.10)
ln(EBITDA/Sales)						0.482				1.868***
						(1.49)				(4.52)
D/V							-2.470			
							(-1.72)			
D/EBITDA								-0.135		
								(-1.95)		
D/EV									-2.219	-5.331**
									(-1.68)	(-3.16)
Observations	6851	6851	6851	6851	6851	6851	6851	6851	6851	6851
Adjusted R-squared	0.019	0.032	0.030	0.020	0.019	0.020	0.020	0.020	0.020	0.036
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix H

Table 1

Regressions Explaining Public Equities taken Private (1997-2017)

This table reports the results of regressions of a binary variable indicating a public equity was taken private on various lagged firm characteristics. Panel A reports results from logistic regressions. Panel B reports results from ordinary least squares (OLS) regressions. The sample consist of the identified PE-backed companies and S&P 500 constituents. The number of observations represents both the PE-funded and the controls. The time period is 1997 to 2017. All specifications include year fixed effects. *z*-statistics are reported in parentheses. Significance levels 10 %, 5 %, 1 % are denoted by asterisks ***, ** and *, respectively.

Panel A: Logistic Regression (1997-2017)

Independent Variables	1	2	3	4	5	6	7	8	9	10
Beta	0.369**									-0.390
	(3.20)									(-1.91)
ln(Sales)		-2.458***								
		(-19.69)								
ln(ME)			-2.886***							-3.449***
			(-17.94)							(-14.64)
ln(BE/ME)				1.073***						0.0881
				(9.32)						(0.61)
ln(EV/EBITDA)					-0.114					0.901***
					(-0.82)					(3.93)
ln(EBITDA/Sales)						-0.710***				1.042***
						(-10.57)				(5.09)
D/V							-0.564			
							(-1.31)			
D/EBITDA								-0.0193		
								(-0.53)		
D/EV									-0.440	-3.752***
									(-1.25)	(-5.94)
Observations	7615	7616	7616	7616	7616	7616	7616	7616	7616	7615
Pseudo R-squared	0.037	0.615	0.700	0.087	0.032	0.063	0.033	0.032	0.033	0.737
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: OLS Regression (1997-2017)

Independent Variables	1	2	3	4	5	6	7	8	9	10
Beta	1.719**									-1.187*
	(2.90)									(-2.42)
ln(Sales)		-7.668***								
		(-23.61)								
ln(ME)			-8.204***							-8.735***
			(-25.74)							(-25.89)
ln(BE/ME)				3.613***						0.212
				(9.95)						(0.56)
ln(EV/EBITDA)					-0.478					3.201***
					(-0.83)					(5.80)
ln(EBITDA/Sales)						-3.558***				1.026**
						(-8.44)				(3.11)
D/V							-2.219			
							(-1.36)			
D/EBITDA								-0.0777		
								(-0.56)		
D/EV									-1.235	-5.507*
									(-1.74)	(-2.52)
Observations	7615	7616	7616	7616	7616	7616	7616	7616	7616	7615
Adjusted R-squared	0.012	0.231	0.274	0.027	0.010	0.023	0.010	0.010	0.010	0.287
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2

Regressions Explaining Public Equities taken Private (1997-2017)

This table reports the results of regressions of a binary variable indicating a public equity was taken private on various lagged firm characteristics. Panel A reports results from logistic regressions. Panel B reports results from ordinary least squares (OLS) regressions. The sample consist of the identified PE-backed companies and S&P 400 constituents. The number of observations represents both the PE-funded and the controls. The time period is 1997 to 2017. All specifications include year fixed effects. *z*-statistics are reported in parentheses. Significance levels 10 %, 5 %, 1 % are denoted by asterisks ***, ** and *, respectively.

Panel A: Logistic Regression (1997-2017)

Independent Variables	1	2	3	4	5	6	7	8	9	10
Beta	0.0799									-0.0652
	(0.67)									(-0.55)
ln(Sales)		-1.580***								
		(-16.76)								
ln(ME)			-1.988***							-2.246***
			(-16.95)							(-15.68)
ln(BE/ME)				0.659***						-0.0648
				(5.38)						(-0.52)
ln(EV/EBITDA)					0.00129					0.531***
					(0.01)					(3.86)
ln(EBITDA/Sales)						-0.382***				0.479***
						(-5.64)				(4.26)
D/V							-0.764			
							(-1.84)			
D/EBITDA								-0.0340		
								(-1.09)		
D/EV									-0.653	-2.243***
									(-1.73)	(-5.91)
Observations	5366	5366	5365	5366	5366	5366	5365	5366	5366	5365
Pseudo R-squared	0.037	0.299	0.387	0.057	0.037	0.047	0.039	0.037	0.038	0.417
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: OLS Regression (1997-2017)

Independent Variables	1	2	3	4	5	6	7	8	9	10
Beta	0.483									-1.510*
	(0.66)									(-2.41)
ln(Sales)		-9.105***								
		(-15.21)								
ln(ME)			-15.04***							-16.90***
			(-22.60)							(-23.44)
ln(BE/ME)				3.554***						-0.734
				(5.74)						(-1.04)
ln(EV/EBITDA)					0.00758					3.964***
					(0.01)					(5.60)
ln(EBITDA/Sales)						-2.448***				2.352***
						(-5.05)				(5.39)
D/V							-4.233			
							(-1.93)			
D/EBITDA								-0.175		
								(-1.21)		
D/EV									-2.688	-10.56***
									(-1.83)	(-4.16)
Observations	5366	5366	5365	5366	5366	5366	5365	5366	5366	5365
Adjusted R-squared	0.014	0.144	0.251	0.023	0.014	0.019	0.014	0.014	0.014	0.275
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes