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Private Equity Transactions: Value Creation through Operational Engineering Evidence from Europe

Victor Heinrich

Technische Universität München

Abstract

This paper investigates private equity value creation strategies through operational engineering. To examine this, I define a KPI framework typically favored by private equity firms. I apply propensity score matching to a dataset of European PE transactions compared to non-PE backed companies to study value creation. By applying a Difference and Difference regression setting and thereby controlling for two-way fixed effects, I can find strong evidence on PE value creation through operational engineering. This paper adds new insights to academia as (a) there are only few contributions using propensity score matching to examine PE value creation and (b) this paper is the first, to the best of my knowledge, to combine the approach of propensity score matching and Difference in Difference regressions, yielding highly significant results on the relevance of EBITDA margin improvement.

Keywords: Private equity; Value creation; Operational engineering; Propensity score matching.

1. Introduction

> *"People used to think that Private Equity was basically just a compensation scheme, but it is much more about making companies more efficient."*
>
> - David Rubenstein[1]

In the last decade, Private Equity (PE) investments in the European Union grew by more than 10% p.a., setting new records by both deal numbers and transaction volume every year.[2] For instance, in 2020, Thyssenkrupp Elevator AG was acquired by PE investors for 17.2 billion Euros which marks the largest PE transaction on the European market.[3] The market grew particularly strong in Europe as it was barely existent in the 1980s, the first boom-phase of PE in the United States (US). Nevertheless, also in the US, the number of PE transactions has almost doubled between 2000 and 2005.[4] Possible causes of the rapid growth in PE transactions are the anticipation of excess returns and lack of alternatives within the strained capital market due to low interest rates and financial crises, especially for institutional investors.

Before describing the PE market and its characteristics in more detail, one should get an overview of the peculiarities of this asset class. Generally, PE is referred to as the acquisition of equity securities in unlisted companies, which is why PE is considered as an alternative asset class. As this usually entails large transaction volumes, PE is primarily used by institutional investors and wealthy individuals.

While PE funds report record-breaking financials in the last years, this was not always the case. The PE industry appears to be subject to strong cyclical fluctuations. Therefore, one should carefully observe this development as the assumption of PE firms creating excess economic value through their actions has become blurred within the last decades, increasingly questioning the high costs associated with PE investments.[5] In addition to the industry's euphoria in recent decades, a growing number of critical voices in the academic discourse have come up questioning the validity of PE firms' business models. For instance, Guo *et al.* interrogate, whether PE transactions are still capable of creat-

[1] Sender (2013) in Financial Times.

[2] See PricewaterhouseCoopers GmbH Wirtschaftsprüfungsgesellschaft, 2020, pp. 18-21.

[3] See Knitterscheidt and Murphy (2020).

[4] See Acharya, Franks, and Servaes (2007, p. 1); Sensoy, Wang, and Weisbach (2014, pp. 1-2).

[5] See Braun, Jenkinson, and Schemmerl (2016, p. 1).

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ing value,[6] Stafford even argues that PE transactions are a scheme for funds to charge high fees as he can replicate their returns with a comparable risk and return pattern using publicly traded securities and homemade leverage.[7] Indeed, the high fees associated with PE investments (mainly attributable to carried interest, management fees, and monitoring and transaction fees) pose additional challenges, as an even higher profit has to be generated to cover these costs.[8]

This paper therefore examines whether PE firms create real economic value by quantifying the operating performance measured by pre-defined key performance indicators (KPI) of 406 leveraged buyouts (LBO) of European based companies between 2013 and 2019. I will also compare these returns with 2,062 transactions from non-PE institutional investors. With this approach, I address the question whether it in fact is PE firms as a "superior form of an organization", as suggested by Kaplan and Strömberg,[9] and the LBO structure that creates surplus value or whether the returns of comparable non-PE backed transaction have a similar KPI development in the years following the transaction. What I am most inquisitive about is whether one can see different pre-buyout characteristics and quantify different development patterns after buyout by matching treatment and control group transactions. This paper therefore contributes to the academic debate on PE value creation in two ways: firstly, by focusing on European-based companies, as previous research predominantly focused on Anglo-Saxon companies and secondly by going beyond the common approach of assessing fund level performance and compare PE-firm to non-PE-backed transactions to assess measures of value creation.

The paper at hand will start with an introduction into the theoretic background of PE as an asset class in chapter 2. Chapter 3 follows with presenting the three main value creation strategies financial, governance, and operational engineering, as defined in academia, and how they can be quantified while also covering critical voices questioning the entire *modus operandi* of PE firms as they might create less value than these firms themselves perceive. After the theoretic framework has been set, chapter 4 will start with developing the research hypotheses to be addressed in this paper. It continues with describing the dataset, the pre-buyout characteristics of the target companies before performing analyses based on propensity score matching (PSM) to compare PE and non-PE transactions. Finally, chapter 5 concludes and discusses the findings, putting them in the framework of academic discourse and giving insights on possible future developments in this industry and avenues for further research.

[6]See Guo, Hotchkiss, and Song (2009, p. 1).
[7]See Stafford (2015, pp. 29-30).
[8]See, for instance, JPMorgan (2021, p. 17).
[9]Kaplan and Strömberg (2009, pp. 130-132).

2. Theoretic Background and Academic Discourse

Between 1990 and 2006, the amounts invested in Private Equity globally has increased fiftyfold and the number of transactions in the US has doubled only between 2000 and 2005 - this untapped growth in number of transactions and thus assets under management appears to have continued steadily in recent years.[10] While having started their first large activities in the 1980s in the US, the PE industry can now be seen as a mature financial sector.[11] This is why it is highly relevant to also approach this topic from an academic perspective. Before chapter 3 covers value creation strategies within the PE industry, this section will address the unique characteristics of PE as alternative asset class. It aims at explaining the asset class itself in chapter 2.1, before section 2.2 will elaborate on the leveraged buyout (LBO), which is the *modus operandi* for most PE transactions. This section closes with a comparison of PE and Venture Capital (VC) as two similar yet distinguishable asset classes within the sphere of alternative investments.

2.1. Private Equity as an Asset Class

PE and alternative investments in general are not uniquely defined. Unlike other alternative asset classes like real estate or currencies, the PE industry is marked by, as the name already suggests, secrecy and often a lack of information on financial figures of companies and transactions. PE firms are usually organized as a limited liability company and act as the general partner (GP) to set up funds which the investors, acting as limited partners (LP), invest in. Usually, PE firms employ highly specialized investment managers and are rather small companies. In fact, PE firms usually are substantially smaller than the companies they target for investments.[12]

Also, within the sphere of PE, one can generally distinguish LBOs and VC as they significantly differ both in what companies are being targeted and how the overall deal financing structure is organized. What is widely referred to as "Private Equity" in academia usually includes LBOs, Growth Capital, and VC.[13] While the transition between the two asset classes is fluent, VC generally refers to investments in less mature private companies. One core idea of VC is to support young and entrepreneurial companies by injecting smaller amounts of equity compared to PE to unleash growth opportunities. This is also why the ticket sizes significantly diverge. Venture capitalists, also alluded to as business angels, bear significantly more risk compared to PE funds since VC usually targets small entrepreneurial companies that do not necessarily have a proven business model or are about to develop it. While the growth potential is huge, so is the

[10]See Acharya et al. (2007, pp. 1-2).
[11]See Puche (2016, p. 5); Sensoy et al. (2014, p. 3).
[12]See Kaplan and Strömberg (2009, p. 123).
[13]See Puche (2016, p. 1).

risk associated to a VC investment. This is also why the expected returns on VC investments of around 40% are significantly higher than for PE investments, with expected returns between 20% and 30%.[14]

Apart from ticket size and the investment's risk and return pattern, the core principle of how these asset classes work, is different. While venture capitalists seek young companies to inject equity for usually a minority stake, PE firms aim at a majority stake or overtaking an entire company with proven and stable business activities while heavily relying on external financing through debt. They do so by employing Leveraged Buyouts as a framework, as extensively displayed in section 2.2. Furthermore, the deal financing structure between PE and VC does significantly differ. While venture capitalists and business angels primarily use equity to invest in target companies, the PE firm's equity stake in LBOs is relatively low.[15] First, PE funds as the GPs raise capital from the committed LPs and secondly use large amounts of debt, which is one characteristic attribute of LBOs.

In line with other publications, I will only include PE-backed LBOs in my definition of PE in this paper.[16] This also has practical reasons, as distinguishing between these two transaction types might be challenging as an identifier it is not included in most commercial databases which ultimately may lead to selection bias.[17]

2.2. PE and its modus operandi: Cyclicality and Buyout Booms

As stated above, PE firms have reached new levels of assets under management. However, this has not always been the case as the entire industry is subject to severe cyclical fluctuations. Acharya *et al.* state that *"(. . .) low interest rate, loose credit conditions and syndication of loans (. . .)"*[18] drive the popularity and amounts of LBOs.

KAPLAN and STRÖMBERG define three major buyout waves in this context: while PE funds first emerged in the 1980s, the first wave lasted for nearly ten years before declining by 1990, again. After this, PE activity significantly increased at the end of this decade, with the second wave peaking in 1998 and finally decreasing with the burst of the dotcom bubble in 2000. The third wave set off in the mid 2000s and reached its climax in 2007 where the PE industry in the US surpassed a valuation of 1% of the US stock market for the first time.[19] Also, due to the low levels of credit spread since 2003, LBOs became even more leveraged and more expensive until the setoff of the financial crisis of 2007/2008.[20]

One reason for this cyclicality is the unique characteristic of PE transactions highly relying on external financing within the framework of an LBO with several special purpose vehicles (SPV). These SPVs are legal entities solely founded as an equity or debt instrument within the transaction. In general, the PE fund as the management company establishes a SPV in the form of a limited liability company[21] and thereby acts as the GP in the investment process. The GP manages the fund and takes all operational decisions while the investor as the LP contributes the equity required besides the debt provided by external credit institutions, which already accounts for 60 to 90% of the buyout price.[22] Besides this classic model, parallel co-investments in a portfolio company through the LP are also possible. This trend became increasingly popular in recent years: while not only the popularity of co-investments grew, some institutional investors also even tend to invest in companies on their own (solo investment) - thereby foregoing the established limited partnership model.[23]

This GP/LP structure has advantages such as the limited liability of the SPVs that are beneficial in the case of negative development of the assets acquired by the fund and impending insolvency. On the other hand, a limited partnership agreement is also associated with high costs for founding and maintaining the SPV ecosystem.

In the framework of a limited partnership, the LPs capital can be drawn whenever the GP has identified a suitable target company. This process of raising capital can be considered as the first phase of the fund lifecycle. Regarding the fund cash flow, the first years of the fund lifecycle where the GP acquires the portfolio companies are marked by negative cash flow because of transaction costs, management fees charged by the GP and maybe even write-offs for failed deals. This period of sourcing the deal flow and targeting firms is the second phase. After the phase of target acquisitions, the fund's third phase of operational improvement takes place ultimately yielding positive cashflows that can be distributed back to the LPs. Finally, the fund lifecycle ends with exiting the investments and divesture. The GP is reimbursed with management fees during the holding period and carried interest while divesture according to contractual agreements that usually include performance hurdles and the committed equity contributions plus capital interest are refunded to the LPs. As one can see, the fund lifecycle starts with negative cashflows and finally yielding positive contributions before ending in divesture. Therefore, one can describe the lifecycle of a PE fund as a so-called "J-curve".

This LBO framework can become rather complex as a single PE firm may use dozens to hundreds of SPVs for a single fund. As they actively engage in every singly portfolio

[14]See Achleitner and Braun (2015, p. 14).
[15]See Achleitner and Braun (2015, pp. 14-15).
[16]See, for instance, Hahn (2009, pp. 12-13).
[17]See Heckman (1979, p. 153).
[18]Acharya, Hahn, and Kehoe (2009, p. 9); See Axelson, Jenkinson, Strömberg, and Weisbach (2012, p. 24); Ljungqvist, Richardson, and Wolfenzon (2008, p. 1).
[19]See Kaplan and Strömberg (2009, pp. 124-127).
[20]See Acharya et al. (2007, p. 3).

[21]For instance, in Germany a GmbH (Gesellschaft mit beschränkter Haftung) or also commonly used the luxembourgish (Société à responsabilité limitée) or dutch (besloten vennootschap met beperkte aansprakelijkheid) equivalents.
[22]See Kaplan and Strömberg (2009, p. 124).
[23]See Fang, Ivashina, and Lerner (2015, p. 160); Braun et al. (2016, pp. 17-18).

company, they try to optimize the business to generate surplus value for the fund and its investors. Therefore, most research in this area has focused on the performance of single funds as this represents the return to the investor.[24] This, however, might not be the best approach. As researchers are often interested in whether (and if yes: how) value is generated by the GP, one should carefully investigate the actions taken by the GP to assess their financial impact on exit valuation. To do this, one needs to focus on deal level data of single transactions. This, however, is even more challenging than evaluating fund level data as it this proprietary information is kept highly secret by the GPs. While most research has covered fund performance, there are only few academic contributions focusing on deal level data to shed light on the value creation process.[25] For this reason, the next chapter will cover value creation strategies applied by PE funds and present the debate in academia.

3. Value Creation in Leveraged Buyouts

The holistic idea of value creation through different levers is at the core of PE fund managers value proposition towards investors. Therefore, it is crucial to methodically understand the value truly generated by fund managers as well as the strategies applied to generate these returns to critically evaluate the risk and return profile associated with alternative and, especially, PE investments. However, the academic discourse on PE value creation is still in an early stage. For this reason, there is no universal tool or generally applicable methodology for measuring overall value creation. With the emergence of PE as an asset class in recent decades, academic interest for this industry and its value creation mechanisms also evolved. In addition to studies investigating fund level performance, few studies on value creation on a deal level arose, though mainly focusing on the US as the largest PE market.[26] Assessing fund performance, however, is not the best suited approach when evaluating the GP's skill on a transactional level as it does not address the question of by which means value verily is generated within a portfolio company that ultimately translates into the fund performance.

Within this discourse of whether to regard performance of a fund or a single portfolio company to assess value creation, some might also argue there is no genuine value creation through LBOs, but only wealth transferred to the GP (value transfer hypothesis).[27] On the other hand, authors also argue that PE ownership does not create any new value, but organizational improvements may lead to increased financial benefits for the LBO stakeholders (value transfer hypothesis). Most empirical studies, however, do confirm that buyout transactions are subject to significant gains in economic value due to an increase in profitability as well as productivity. Other studies, however, also confirm this value creation hypothesis. As can be seen, the academic discourse on this debate is inexhaustive and a range of vantage points and opinions on the PE value creation process have emerged.

Nonetheless, in most cases value increases are caused by a mixture of both value transfer and value creation which is difficult to disentangle into its distinct underlying value drivers. Therefore, Achleitner et al. (2010) pioneered in this area of research and developed a comprehensive framework for methodologically capturing and decomposing the economic value created within a PE transaction using a deal level data set from European buyout transactions: by unlevering returns, one can decompose PE deal returns into their sub-parts, which the authors refer to as the *Value Creation Bridge*. From this, three overall strategies could be employed to achieve increased value: financial, operational, and governance engineering, as displayed in Figure 1.[28]

Besides the levers identified by Achleitner *et al.*, value capturing refers to an increase in value without any changes in financial performance and may occur due to negotiation skill at the time of buyout and divesture. However, the two primary and one secondary levers displayed in Figure 1 do have a direct bottom line effect and lead to direct value creation through the actions taken and implemented.[29] The differentiation into these three main value creation pathways also is widely accepted in academia[30] and can be split into distinctive drivers for each value creation pathway. While financial engineering covers factors mainly implied by the leverage effect, operational engineering focusses on actual improvements due to operative and strategic advice as well as actions imposed by the GP. Thus, the latter effect, namely increasing EBITDA[31] and free cash flow (FCF), does require skill and specialized expertise by the GP. The highly relevant EBITDA effect can also be further decomposed into effects resulting from increased sales and margins. Within the operational engineering framework, also multiple and combination effects are considered. However, as the value creation bridge aims at mathematically decomposing returns, it neglects potential effects of interdependencies and other, unobserved effects. Therefore, governance engineering might be adopted as an overarching strategy. This value creation driver refers to the impact of expanded and optimized monitoring and governing mechanisms within the portfolio company to decrease agency costs.[32]

Given these interdependencies between value creation drivers and the current academic discourse, the next chap-

[24] See Achleitner, Braun, Engel, Figge, and Tappeiner (2010, p. 17).
[25] See Achleitner et al. (2010, pp. 17-18); Acharya et al. (2009, pp. 7-9).
[26] See Achleitner et al. (2010, p. 1, p. 17); Kaplan (1989a, pp. 218-219); Guo et al. (2009, pp. 1-2); Cohn et al. (2020), p. 258; Kaplan and Schoar (2005, pp. 1791-1792); Phalippou and Zollo (2005, p. 2).
[27] See Lowenstein (1985, p. 731).
[28] See Achleitner et al. (2010, p. 18-19).
[29] See Berg and Gottschlag (2003, p. 7).
[30] See Gompers, Mukharlyamov, and Mukharlyamov (2015, pp. 2-3); Kaplan and Strömberg (2009, pp. 130-132); Berg and Gottschlag (2003, pp. 4-9).
[31] EBITDA - Earnings before Interest, Taxes, Depreciation and Amortization
[32] See Biesinger, Bircan, and Ljungqvist (2020, pp. 8-9); Gompers et al. (2016) p. 3.

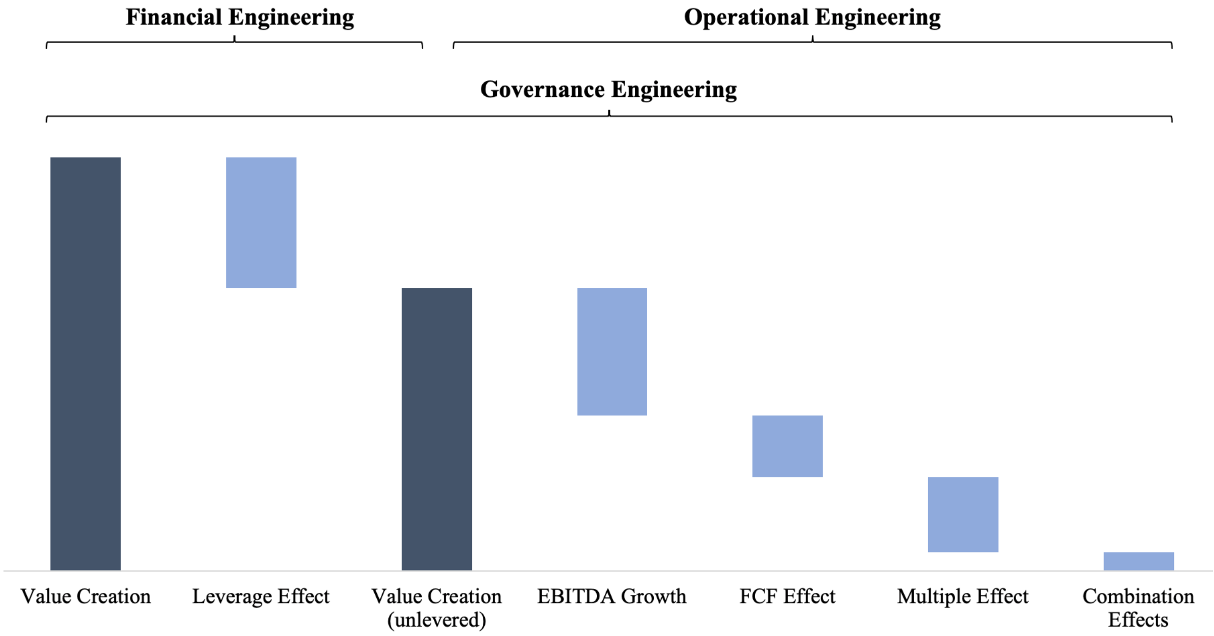

Figure 1: Value Creation Bridge according to Achleitner *et al.*

Own representation based on Achleitner et al. (2010, p. 19).

ters will present strategies and academic findings for each of the three major value creation pathways.

3.1. Financial Engineering

Financial engineering is one unique attribute of LBOs as it refers to the value creation through external financing. Value creation through financial engineering can best be thought of as a value shift enabled by altering the capital structure, primarily via the use of debt, on the portfolio company's balance sheet.[33] The relevance of financial engineering is even stronger in times of low interest rates, as could have been seen in recent years: *"when credit is abundant and cheap, buyouts become more leveraged"*[34]. By using leverage, companies can lower their capital costs in terms of weighted cost of capital (WACC) and are able to maximize the valuation multiple at the time of exit. Also, decreasing WACC by taking on more debt is cheaper than the costs of the investor's equity, yielding excess returns, and therefore posing the predominant form of deal financing in LBOs.[35]

Besides this, increased debt allows firms to leverage their operating earnings and make use of tax-shield effects to increase the return on invested capital. By reducing taxable income from higher interest and depreciation deductions due to debt repayments, substantial additional value can be generated that can be quantified and translated into higher exit valuation multiples.[36] This effect can even be reinforced when the GP is capable of perceiving market inefficiencies and arbitrage opportunities unveil: Engel, Braun, and Achleitner (2012) show that PE firms in fact have access to underpriced debt for buying equity and profit from this by capitalizing potential market inadequacies between debt and equity market and exploiting their superior information about the target company.[37] While there are academic contributions showing high levels of leverage at buyout with continuous de-levering throughout the holding period, suggesting PE firms in fact exploiting these market inefficiencies,[38] other papers find no clear evidence on leverage development patterns throughout the observation period.[39] Some authors even argue that this exploitation of market inefficiencies set the start for the ever-growing buyout boom of the early 2000s that finally collapsed or even led to the credit market turmoil and the financial crisis starting in 2007.[40]

In turn, increased leverage goes along with a higher risk, which is why an investor as a *homo oeconomicus* may demand a risk premium for higher leverage in a buyout scenario.[41] Additionally, PE is a rather illiquid asset class. Compared to, for instance, publicly traded securities, an investor would therefore, *ceteris paribus*, demand an illiquidity premium for an investment in this asset class.[42] This is also why recent academic contributions usually define financial engineering

[33] See Berg and Gottschlag (2003, p. 7, p. 19).
[34] Axelson et al. (2012, p. 32).
[35] See Guo et al. (2009, p. 27).
[36] See Kaplan (1989b, p. 630-631); Lowenstein (1985, p. 759).

[37] See Engel et al. (2012, p. 487); Berg and Gottschlag (2003, pp. 14-16).
[38] See Achleitner, Braun, and Engel (2011, p. 5).
[39] See Stafford (2015, p. 11, p. 16).
[40] See Kaplan and Strömberg (2009, p. 122).
[41] See Achleitner et al. (2011, p. 3).
[42] See, for instance, Stafford (2015, p. 25-26); Harris, Jenkinson, and Kaplan (2013, p. 4).

as one major driver in PE value creation yielding excess returns. In line with this, leverage effect is supposed to account, depending on the sample and methodology applied, for around 20% to 30% of overall economic value generated in the transaction.[43] However, some studies also find evidence that GPs tend to enter overpriced agreements the more leverage they can use, resulting in lower returns.[44] I can generally distinguish two main results of highly levering a target company: on the one hand, an already profitable company might suffer from financing constraints and therefore lacks capacity to carry out promising and net present value positive investment opportunities. With the capital injected through an LBO, the target company would be able to relax these financing constraints and unleash its growth potential. On the other hand, PE firms might also invest in struggling firms and use the equity to recover the business and capitalize on the business model.[45]

Besides these empirically profound findings just discussed, value creation cannot solely be explained with financial engineering.[46] Also, the relative importance of financial engineering seems to have declined in recent years: while transactions in the early stage of PE activity in the 1980s heavily relied on leverage and governance mechanisms as source of excess returns, portfolio company processes nowadays are typically optimized and enhanced through operational improvements.[47]

It therefore is important to identify additional drivers associated with unlevered private equity value creation. In particular, the origination of the excess returns, which is the difference between the unlevered return of the portfolio company and the unlevered returns of a suitable reference group, i.e., similar companies or industry returns, is relevant for further investigation.[48]

3.2. Governance Engineering

The value creation bridge introduced by Achleitner *et al.* tries to disentangle monetary returns in a quantitative way. However, due to the nature of this concept, it neglects other perspectives that might be worth considering as it might unfold effects across different sections of the framework. As there might be an overlap in the sources of value creation,[49] governance engineering can best be described as an overarching layer addressing all residual value drivers and business processes within an LBO, while not having a direct bottom-line impact.

This value creation strategy refers to effects of increased and optimized supervision and governance mechanisms, the so-called secondary layers, within the portfolio company to reduce agency costs.[50] These secondary levers do not necessarily have a direct bottom line impact but increase it through interactions with the primary levers.[51] Like in publicly traded firms, where executives often receive (virtual) shares and stock options as part of their compensation, this may align interests of different stakeholders and ultimately reduces agency costs. Also, it is quite common to replace the entire management team after a buyout which is one example to what extent PE firms are involved in the newly acquired portfolio company.[52]

Furthermore, standardized planning and monitoring can result in increasing sales volume and profitability, which ultimately creates surplus value.[53] One reason why these governing mechanisms are implemented more successfully in portfolio companies than, for instance, in family businesses is the GP's expertise in the PE sphere or a specific industry. One possible explanation for this are the academic findings that PE excess returns usually are time persistent.[54] This means that the GPs who successfully implement these overarching secondary layers can reduce agency costs within cash flow relevant processes. Apparently, not every PE fund can do so which is why the successful funds seem to have skill rather than pure luck as they can show excess returns continuously across vintage years.[55]

3.3. Operational Engineering

While financial engineering was the primary source of value creation in PE's *"early stage"*, the late 1980s, both practitioners and researchers nowadays mainly focus on actual measures imposed within the portfolio company by the GP. Through these actions, commonly referred to as operational engineering, the PE firm intervenes in the business processes and strategically optimizes them.[56] In fact, most modern and successful PE firms do focus on certain industries which leads to access to industry experts and special knowledge through the GP's network which reinforces the relevance of operational engineering.[57] Today, operational engineering due to operative and strategic advice and improvements actions imposed by the PE firm is the prevailing value creation strategy,[58] in some cases even resulting in abnormal performance[59].

ACHLEITNER *et al.* find that the shift towards operational engineering is even stronger on the European market and accounts for almost half the value created. They identify two

[43] See Achleitner et al. (2010, p. 25).
[44] See Axelson et al. (2012, p. 1).
[45] See Cohn, Hotchkiss, and Towery (2022, pp. 270-271).
[46] See Achleitner et al. (2010, pp. 17-19).
[47] See Kaplan and Strömberg (2009, pp. 132-133); Puche (2016, p. 41).
[48] See Acharya et al. (2009, pp. 14-15); Puche (2016, p. 20).
[49] See, for instance, Guo et al. (2009, p. 3).
[50] See Biesinger et al. (2020, pp. 14-16); Gompers et al. (2015, p. 5); Berg and Gottschlag (2003, pp. 24-30).
[51] See Berg and Gottschlag (2003, p. 24).
[52] See Anders (1992, pp. 8-12).
[53] See Biesinger et al. (2020, pp. 1-2).
[54] Acharya et al. (2009, pp. 11-23).
[55] See Berg and Gottschlag (2003, p. 17, p. 29); Johan and Zhang (2021, p. 217); Jensen (1986, pp. 328-329).
[56] See Graf, Kaserer, and Schmidt (2009, p. 15).
[57] See Kaplan and Strömberg (2009, p. 135); Graf et al. (2009, p. 15).
[58] See Achleitner et al. (2010, pp. 25-26); Harris et al. (2013, p. 20); Kaplan and Strömberg (2009, pp. 131-132).
[59] Achleitner et al. (2010, pp. 25-26); Acharya et al. (2009, pp. 23-24).

major effects within the value creation bridge to capture operational effects: EBITDA growth and the FCF effect, where the latter is mainly affected by working capital optimization, investments, tax, debt (re-)payments and EBIDTDA growth. Also, the excess multiple expansion (defined as the multiple effect that incorporates the change in valuation multiple between entry and exit) represents a fundamental factor in explaining equity returns through operational engineering as a result of a PE fund manager's skill rather than pure luck or macroeconomic fixed effects. As both EBITDA and multiples do have an impact on enterprise value (EV), a correcting factor is added to eliminate effects stemming from the aforementioned value drivers.[60]

Other authors argue that a more efficient usage of existing assets and excising unproductive ones requires skill and therefore is one major underlying sources of operational effects.[61] This reinforces the argument of skill: through efficient cost-cutting measures and strategic decisions taken by experts, value can be generated that exceeds the benefits created through financial engineering. However, literature also presents ambiguous results on operational engineering. While some studies find little to no evidence for operational improvements, most authors do find evidence for it, especially in Europe.[62]

Several authors find significant evidence for increases in operating performance during the first buyout wave in the US in the late 1980s. Kaplan found that his sample of public-to-private transactions systematically outperformed the market through EBITDA growth.[63] Other authors also report findings that are in line with this.[64] On the other hand, more recent studies show a blurred picture: while Acharya *et al.* report significant increases in EBITDA and sales growth, Guo *et al.* see a negative trend after buyout.[65] In summary, operational engineering drivers have had a significant impact on value creation throughout the first buyout wave in the late 1980s. While this value driver appeared to become more relevant also in the 2000s, most funds adapted this strategy and shifted their focus from value creation through excess leverage to value creation through operational improvements within the portfolio companies and the optimization of governance mechanisms.

However, operational effects do not always seem to be clearly significant within the process of genuine value creation. As the relative importance of financial engineering has decreased, governance mechanisms must have gained in relative importance. Alternatively, other KPIs are being improved by "modern" GPs so that the older approaches to capture this value creation cannot account for them. The value creation bridge introduced by Achleitner *et al.* may nevertheless offer a powerful tool to do so.

[60]See Achleitner et al. (2010, pp. 18-19).

[61]See Guo et al. (2009, p. 2).

[62]See Acharya et al. (2009, p. 12); Guo et al. (2009, p. 17); Achleitner et al. (2010, pp. 20-23); Achleitner et al. (2011, pp. 14-25).

[63]See Kaplan (1989a, pp. 250-251).

[64]See Harris et al. (2013, p. 27).

[65]See Guo et al. (2009, p. 28); Acharya et al. (2009, p. 25).

3.4. Why Private Equity Performance is also critically reviewed

Besides the authors who are decomposing value creation and certifying value generation through different levers, one can also observe that the performance persistence of PE as a "superior asset class" is not as clear today as it was in its evolving phase during the 1980s.[66] Results of more recent contributions have shifted the clarity of results - some authors even take a completely different point of view.

LOWENSTEIN, for instance, introduced the concept of the value transfer hypothesis, stating that through an LBO no new value is generated but only transferred to the GP.[67] As discussed above, recent studies find mixed results in terms of value creation especially since the second buyout wave's setoff. Some papers suggest that there is little value creation in PE-backed transactions,[68] other authors even go a step further: STAFFORD showed quite impressively that it would be possible to replicate a portfolio with the same risk and return pattern as a PE fund using homemade leverage and hold-to-maturity accounting. This portfolio with publicly traded securities in fact outperformed PE returns, even before fees, leading to the conclusion that PE does not create surplus economic value and PE investors either take way more risk on than they realize or have severe internal agency conflicts leading to inefficient asset allocation.[69] In line with this, concerns also may arise from return smoothing policies applied by PE firms. Given the assets illiquid nature and that they are not publicly traded, the GP alone values the portfolio company. This allows the PE firm to understate the factual market exposure and thereby artificially downsize portfolio volatility. While this practice can be observed in (hedge) funds, it is very likely to be even more present in private transactions given the industry's secrecy and lack of public reporting requirements.[70]

Therefore, one may wonder why PE is once again on the rise, given investing in this asset class is associated with high costs and uncertainty as well as long holding periods and thus illiquid in nature. Is it only the need for diversification in a low-interest rate environment that drives demand for PE investments? Generally, PE activity rises when interest rates are low as it loosens the credit limits and allows to leverage a portfolio company even more.[71] Also, other asset classes like real estate become more expensive the lower the interest rates are, which may explain the buyout waves of the 1980s and 2000s. However, this trend does not explain whether value is generated through these transactions.

[66]See Braun et al. (2016, p. 1).

[67]See Lowenstein (1985, p. 731).

[68]See Guo et al. (2009, p. 1).

[69]See Stafford (2015, pp. 2-5, p. 28).

[70]See Asness, Krail, and Liew (2001, p. 13); Stafford (2015, p. 4).

[71]See Axelson, Jenkinson, Weisbach, and Strömberg (2008, p. 18, pp. 22-23).

4. Data Analysis

As seen, contrary findings on value creation strategies in LBOs exist. Especially, as the practical relevance of leverage has declined since the 1980s, recent literature finds mixed results on operational effects. Thus, research in the sphere of value creation through operational engineering seems worthwhile to follow. Also, academia appears to lack deal-level information on European transactions, as most literature focusses on fund-level data in the Anglo-Saxon area. Other authors even critically challenge the entire concept of PE investments by simply replicating their returns with a comparable risk and return pattern foregoing the classic GP/LP partnership structure. From this discourse I want to derive the following research question:

> *Are PE-backed transactions in Europe more heavily influenced by operational engineering value creation strategies than non-PE-backed transactions?*

To address the research question, I will formulate three hypotheses that will be tested in this chapter. In this context, section 4.1. develop the hypotheses by motivating and justifying them, before describing the data set and its properties. Chapter 4.3. will give a descriptive overview of the data and will compare treatment and control group characteristics. Section 4.4. will elaborate on the research design and present the methods applied before chapter 4.5. will finally outline the results and findings.

4.1. Hypothesis Derivation

The main question at hand when assessing PE performance nowadays is whether PE funds genuinely create economic value through their actions. I would therefore expect to find significant differences in financial characteristics when comparing LBOs and non-PE backed transactions. Furthermore, given PE firm's intensive commercial and operational due diligence efforts, it also is conceivable that control group transaction and PE firm targets' financial characteristics differ pre buyout. I therefore formulate the first research hypothesis as follows:

> H_1: The KPIs of PE target firms and control group transactions differ significantly pre-buyout.

To evaluate H_1, several metrics might be relevant. With the separation of value creation into financial and operational engineering as suggested by Achleitner *et al.*, amongst others, it seems reasonable to take the operational factors into closer consideration as these are drivers, namely improvements in EBITDA and FCF, are influenced by the GP's action during the holding period.[72]

However, leverage might still have a non-neglectable effect on value creation. For this reason, this KPI will be taken into initial consideration, too. To get an estimate of the firm size, also metrics for size and profitability are relevant. For this reason, I consider logarithmized assets (lnAssets) and sales as a size approximator and EBITDA/sales and FCF/sales margin as profitability parameters. In terms of profitability, companies with overall low levels of profitability might less likely be targeted by a PE investor. On the other hand, comparably unprofitable firms could offer more potential for operational improvements and thereby offer opportunities for value creation. On the contrary, a firm with above average profitability might also not be the desirable target company as it becomes increasingly challenging to capitalize on market momentum and participate in future sales and profitability growth.[73] Thus, I will evaluate the selection pattern used by PE firms with this set of KPIs. Focusing on these KPIs also is judicious for other reasons: first, EBITDA is suitable as a measure for comparing a company's performance. Unlike net income, EBITDA it is not distorted by interest, tax, depreciation, and amortization and thus depicts a company's operational earning capabilities.[74] Therefore, EBITDA can be used to assess a firm's ability to repay debt, a very important information in an mergers and acquisitions setting with highly levered transactions. On the other hand, FCF might be more suitable to assess a company's real valuation, as it is unencumbered. Also, increases in FCF are driven by decreasing capital expenditures (CapEx) and increasing operating income, which captures the potential effects of operational engineering well.[75]

Besides the comparison of pre-buyout characteristics, it is detrimental to observe their development throughout the observation period. If H_1 was to hold true, PE firms would make use of a specific target selection pattern to ultimately generate excess returns through operational engineering. I would therefore expect the PE-backed companies to evolve differently throughout the observation period in terms of EBITDA and FCF as well as profitability than the control group transactions as these KPIs can be perceived as the main drivers of value creation through operational engineering. Following this, I should be able find significantly different KPI developments at a defined level of certainty. I therefore formulate hypothesis two as follows:

> H_2: PE firms do have a target selection pattern based on a set of KPIs that is different to non-PE firms. These KPIs evolve disparately throughout the observation period.

Given the relevance of operational engineering in European transactions, EBITDA and FCF and their post-buyout development are the relevant factors for further evaluation. To account for size-fixed effects, also their sales margins are to be considered.[76] Given the skill and knowledge PE firms apply to create excess economic value through operational engineering, deals backed by PE firms should outperform non-PE

[72] See Achleitner et al. (2010, pp. 18-19).

[73] See Acharya et al. (2009, p. 18).

[74] See Acharya et al. (2009, p. 13).

[75] See Jensen (1986, p. 323, pp. 327-328).

[76] See Cohn et al. (2022, pp. 274-275).

transactions in terms of the above-mentioned KPIs. I therefore formulate my third and last hypothesis:

> H_3: There is a stronger growth in profitability and KPI improvements within the PE-backed treatment group than in the control group. This increase is attributable to operational engineering measures.

These hypotheses will be addressed in chapters 4.3. to 4.5, after the data set and its characteristics have been introduced in the next chapter.

4.2. Data Collection

As there is abundant literature on the deal level data sets in the US, the aim of this paper is to examine performance on the transactional level through operational engineering in European transactions, the second-largest market for PE investments after the US. However, it is not trivial to collect financial data covering deal level PE transactions as the target companies usually do not have to publicly disclose their balance sheets and financial reports and the PE firms being utterly secretive. This complicates retrieving reliable, correct and up to date financial data.[77]

For this reason, I collected two data sets from Bureau van Dijk's Orbis database based on balance sheet and cash flow statement information for each financial year available. With these datasets I can analyze deal-level data as I can calculate KPI developments on a company-level from single financial statements line items (FSLI). I collected two datasets for comparison and analysis: the first contains deal-level data on PE firm-backed LBOs, which I will refer to as the treatment group. The second data set, the control group, contains financial data on non-PE backed transactions. My main sample contains transactions from Austria, France, Germany, Great Britain, Italy, and Switzerland - as the largest economies in Europe and the European G7 countries, amended by Austria and Switzerland for the geographic German speaking GAS region. The final sample includes transactions closed between 2013 and 2019 as this period is in line with the data availability in Orbis. Following Kaplan *et al.* and Guo *et al.*, I will focus on a timeframe before and after the buyout: The year before the buyout (T-1) until two years after the buyout (T+2).[78]

After collecting the data, I manually performed some initial tidying activities before importing the datasets to R Studio.[79] The final sample only includes transactions for which I can calculate all KPIs necessary for further analysis (EBITDA, FCF, assets, and leverage) for the entire observation period. As commercial databases regularly contain self-reported or estimated numbers,[80] I will also only include officially reported financial statements. I excluded non plausible entries such as negative values for sales and converted FSLIs in other currencies into Euro given the year-end exchange rates reported by the European Commission.[81]

After the data is cleaned, I calculate the relevant KPIs from the balance sheets and profit and loss statements for further analysis. To follow the concept introduced by Achleitner et al. (2011) and other authors, I will mainly focus on EBITDA and FCF as KPIs influenced by operational engineering. As the sample consists of deals from different countries, reporting standards and therefore KPIs reported by a company may not always be comparable. Also, neither EBITDA nor FCF are uniquely defined according to generally accepted accounting principles (GAAP) or international financial reporting standards (IFRS),[82] which is why I will use Orbis' KPI definition and calculate the KPIs from the relevant FSLIs.[83] All KPI calculations and definitions used within the course of the next chapters are decomposed in *Appendix 1*.

After I have calculated the KPIs, I added dummy variables for treatment status (treatment vs. control group), buyout year, target country and industry. Overall, Orbis includes 25 default industry classifications. For reasons of simplicity and to avoid potential overfitting of the regression models to follow due to too many dummy variables, I synopsize these subindustries according to a five-industry classification based on the framework introduced by *Fama and French*.[84] The assignment of SIC codes to the five industry types is displayed in Appendix 4. These industries are:

- FF1 Consumer durables (wholesale, retail etc.)
- FF2 Manufacturing, energy, and utilities
- FF3 High-tech, business equipment, telephone, and television transmission
- FF4 Healthcare, medical equipment and drugs
- FF5 Other

To account for outliers, I winsorized the data on a 5% confidence level after the dataset has been imported into R for further analysis. The effect of winsorization on the data distribution is depicted in Appendix 5 Given the data availability and the assumptions made I dropped Switzerland as an observation country since after data wrangling no treatment group transactions remained. For the same reasons, no transactions in 2013 and 2014 remained. After this data manipulation for cleaning purposes was completed, the datasets contained 406 treatment group deals and 2.062 control group transactions carried out between 2013 and 2019. An overview of the final dataset is given in Table 1.

With this information as a starting point of the data sets' structure, the next section will start with descriptive analyses, already partially addressing the research hypotheses, before section 4.4. will use more in-depth statistical procedures to postulate causal relationships and answer the research question.

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[77] See, for instance, Graf et al. (2009, p. 2).
[78] See Kaplen et al. (1989), p. 235; Guo et al. (2009, p. 51).
[79] See Wickham (2014, pp. 2-5).
[80] See Harris et al. (2013, p. 7)
[81] See European Commission.
[82] See Hahn (2009, p. 24).
[83] See Beuselinck, Elfers, Gassen, and Pierk (2021, p. 10).
[84] See French's website for more detailed information on industry classification.

Table 1: Treatment and Control Group Characteristics

	Treatment Group	Control Group
FF1	125	503
FF2	88	459
FF3	43	298
FF4	13	78
FF5	136	716
Austria	3	19
France	94	465
Germany	37	242
Italy	123	666
UK	149	670
2015	76	458
2016	102	439
2017	92	496
2018	123	599
2019	13	70

Characteristics of treatment and control group transactions: main industry based on *Fama French* five industries classification, target country and buyout year for the cleaned treatment and control group dataset.

4.3. Descriptive Statistics

My two data sets will be introduced with an overview of KPI levels before comparing treatment and control group transactions in this section. Finally, I will also display first findings on KPI development throughout the observation period. On average, a PE target company has a pre-buyout (T-1) EBITDA of 10.6 Mio. EUR and FCF of 7.4 Mio. EUR while the control group seems to have a lower EBITDA (mean 6.7 Mio. EUR) and FCF (mean 5.2 Mio. EUR).

In addition, a more detailed overview of KPIs for both treatment and control group throughout the observation period is graphically displayed in Appendix 2 as well as presented in Appendix 3. As one can see from this overview, the KPIs driving value creation through operational engineering as defined above do appear to differ. Not only in terms of differences between treatment and control group, but also in terms of skewness - the clear discongruity between median and mean as seen above is only a first indicator for diverging selection patterns between treatment and control group. Besides this, PE transactions also seem to be larger in size (measured by lnAssets) than the control group (mean of lnAssets in T-1 was at 10.41 for the treatment group and 8.09 for the control group). These findings are in line with other author's findings and could give an initial indication to confirm hypotheses one and two.[85]

It has become apparent that the key parameters considered do differ pre-buyout. From this, however, I cannot deduce a significant indication for PE target selection patterns. Therefore, I first apply a t-test on means between treatment and control group transactions.[86] However, the data distribution violates the tests prerequisites of homoscedasticity and normality.[87] In fact, the dataset retrieved from Orbis appears to be comparable to the one used by Acharya *et al.* in distribution as the KPIs are not normally distributed and are left-skewed as well as leptokurtic.[88]

Given the data sets' peculiarities, I conduct Wilcoxon's signed-rank test to test for differences in the median between test and control group, as this test is less sensitive for outliers than a *regular* t-test on means.[89] Setting the treatment group KPI means as the test variable, the null hypothesis of the medians being sufficiently similar can be rejected on a five percent confidence level for all KPIs at least once in T-1 or T0. To assess the strength of the effect, I calculate *Cohen's D* as a measure for effect size.[90] Overall, treatment group transactions appear to be significantly larger in terms of EBITDA, FCF, and lnAssets throughout the observation period, as can be seen in Table 2.

It becomes apparent that the KPI characteristics do differ significantly for most observations. In fact, PE target companies seem to be larger in terms of EBITDA, FCF and assets. Also, unlike control group transactions, leverage appears to increase for treatment group transactions, which is plausible due to the LBO structure.[91] To be able to carry out the analyses to follow in chapter 4.5., I first try to capture tendencies in KPI development for both control and treatment group sep-

[85]See Acharya et al. (2009, p. 15-17).

[86]See Student (1908, p. 1).

[87]The prerequisites were tested using Levene's Test for equal variances to test for homoscedasticity and Shapiro Wilk Variance Test for normality, see Levene; Shapiro and Wilk (1965)

[88]See Acharya et al. (2009, p. 16).

[89]See Dalgraad in Introductory Statistics with R (2008), p. 99. and Acharya et al. (2009, p. 16).

[90]See Cohen (1988, p. 20-21).

[91]I.e., more debt is taken on in T+2 for financing of additional net present value positive projects to, for instance, implement market expansion strategies developed together with the PE firm.

Table 2: Wilcoxon Signed Rank Test on Median

KPI Median	Wilcoxon Signed Rank Test on Median			
	T-1	T0	T+1	T+2
EBITDA	4,428.27*	4,291.80*	4,660.52*	4,051.80*
	*1,614.38**	*1,417.40**	*1,594.69**	*1,468.07**
	(0.29)	(0.27)	(0.25)	(0.27)
FCF	3,129.98*	2,477.78*	998.54	1,552.34
	*1,304.26**	*848.09**	*974.63*	*875.45*
	(0.15)	(0.17)		
lnAssets	10.19*	10.34*	10.57*	10.60*
	*7.91**	*7.96**	*8.06**	*2.65**
	(0.95)	(0.99)	(1.00)	(1.01)
Leverage	42.42%	40.86%*	38.80%	57.46%*
	41.21%	*33.97%**	*33.60%*	*33.14%**
		(0.13)		(0.08)

Wilcoxon Signed Rank Test on the median of treatment and control group. The numbers represent the median for EBITDA and FCF in TEUR. Significant differences in median on a 5% confidence level are denoted with an asterix. Figures in *Italics* state the values for the control group. Added in parentheses is the effect size, if the difference is significant, measured by *Cohen's D*.

arately. I therefore compare the development of KPI growth between treatment and control group transactions throughout the observation period. The results are presented in Table 3.

From this it becomes clear that treatment and control group transactions do not only differ significantly in their pre-buyout characteristics, but they also evolve differently throughout the observation period.

From the initial analyses performed in this chapter, it became clear that in fact there is a significant difference value driving KPIs both pre-buyout as well as afterwards. Besides this, I could also find initial evidence on pre-buyout differences between PE-backed and control group transactions. All the above does in fact suggests initial evidence for the research hypotheses postulated above. For this reason, the next chapter will address these questions in more depth, using a virtually pioneering approach in the sphere of PE research: matching treatment and control group transactions via propensity score matching (PSM) based on their pre-buyout KPI characteristics.

4.4. Research Design

To fully address the hypotheses and ultimately ascertain causal relationships, I will illustrate the methods applied, mainly propensity score matching, in this chapter before section 4.5. will present the results. Overall, PSM describes the matching of two populations using propensity scores (PS) estimated by a logistic regression model. While this approach is a standard procedure in scientific areas where observational studies are predominant (i.e., psychology or medicine), Acharya et al. (2009) were, to the best of my knowledge, the first authors applying this method to performance driver quantification in PE investments.[92] This strategy is particularly intriguing as it introduces new approaches to an existing academic discourse: while there is numerous contributions on PE target selection patterns and PE target performance post-buyout, this method incorporates both streams of literature.

Using this approach, I can compare KPI development with very similar pre-buyout characteristics and a comparable PE buyout likelihood, expressed by the estimated PS.[93] Consequently, I can investigate the effects of PE ownership in comparison to the control group transactions. In addition, PSM incorporates further benign characteristics: as I can reduce selection bias, amongst other biases associated to covariates, by applying PSM in combination with an effective matching algorithm, I can testify relationships without having to consider potential shortcomings weakening my analyses' testimonies as extensively.[94] Furthermore, matching based on the calculated PS allows me to assume the groups to be sufficiently alike and matched transactions to be interchangeable between treatment and control group. Precisely this exchangeability is crucial for causal inference and thus for me to derive causal and statistically significant conclusions from the analyses to be performed in the next chapter. This interchangeability therefore also allows me to presume adequately similar KPI characteristics between control and treatment group. Although the number of control group transactions is noticeably larger, this substitutability in combination with the above unveiled statistically significant inter-group

[92] See Rosenbaum and Rubin (1985, p. 38); Acharya et al. (2009, pp. 14-22).

[93] The PS can be interpreted as the likelihood of the target company being treated, id est, undergoing a PE-backed LBO.

[94] See Acharya et al. (2009, p. 16).

Table 3: Overview of pre-Buyout KPI Characteristics and Development

	T-1 to T0	T-1 to T+1	T-1 to T+2
EBITDA	-402.62	723.44	322.17
EBITDA Margin	3.46%*	3.40%*	1.60%*
FCF	-7,548.19*	-6,017.26*	-5,767,84*
FCF Margin	-23.98%	-24.13%	-12.80%*
lnAssets	0.16*	0.29*	0.39*
Leverage	-9.20%	-15.79%	-8.28%
Sales	3,460.69*	10,080.45*	14,422.83

KPI development throughout the observation period. Displayed in all cases is the mean growth for treatment group transactions. In addition, t test on differences in means between treatment and control group, denoted with an asterix (*) if significantly different on a 5% confidence level. EBITDA, FCF, and sales in TEUR.

differences for pre-buyout KPIs enables me to draw conclusions from analyses based on the matched dataset.[95]

As the prerequisites of PSM appear to be favorable and fulfilled by my dataset, I determine the difference in means of the pre-treatment covariates as a first step. As already in chapter 4.3., this t-test shows, as expected, a significant difference in covariate means. Thus, I continue by running a logistic regression model on the data with the treatment dummy as the dependent and EBITDA margin, FCF margin, lnAssets, leverage, in the buyout year as the explanatory variables to estimate the PS. In addition, I include an industry classification factor dummy variable. The logit model used is displayed in Appendix 10.

While the FCF margin can be interpreted as the quality of a firm's profits, the EBITDA margin accounts for how efficiently the management utilizes the company's resources to generate a return. Thus, the margins represent how many units of FCF, or EBITDA are generated per additional unit of sales. These return on sales figures are well suited to assess operating performance as, unlike for instance return on assets as another widely used KPI, they are not subject to write-ups and write-downs of assets or changes in reporting mechanisms at the time of buyout; this is also why studies applying a similar approach like this paper rely on these KPIs.[96] By choosing these explanatory variables I can account for several factors simultaneously: Leverage represents potential influences of financial engineering while lnAssets controls for firm size, since smaller companies generally generate higher returns, thus being associated with a higher risk of default. Lastly, the introduced margins act as a link between size and returns given they are scaled on sales and should therefore be comparable within peers.

Having performed the underlying logit model, the region of common support of propensity scores for treatment and control group spans from a 0.10 to a 0.94 PS with a mean for the treatment group of 0.68 (control group 0.47) and a median of 0.71 (control group 0.50). The area of common support and PS distribution are also displayed in Appendix 7. The visual inspection once again indicates significant differences in buyout likelihood between both groups: while the control group's PS distribution is evenly distributed with a tendency towards a normally distributed population, the treatment group PS distribution is clearly left skewed. However, a different treatment group PS distribution would, in fact be surprising, given the factual PE involvement.

Based on these propensity scores, a k-nearest-neighbor matching algorithm is executed and assigns sufficiently similar transactions to each other while reducing overall sample-wide distance between PSs. With greedy matching, I receive 400 matched pairs - the remaining control group items would increase overall distance between sample pairs and are therefore discarded off. To assess the quality of the matching algorithm executed, I gauge the PS distribution and the balance of regression covariates. In fact, both PS distribution and covariate balance could have been improved through PSM, as displayed in Appendix 9. From this it becomes apparent that PSM and discarding off unused control transactions did in fact increase similarity within both datasets and the degree of numerical imbalance between the covariates could have been significantly reduced. Thus, PSM was carried out successfully. The indicative results achieved via the regression analyses performed in chapter 4.3 above can therefore be reconfirmed. This can also be seen by the impact of considered KPIs on PS displayed in Appendices 11 and 12.

Based on the matched dataset created through PSM, I will set up additional logistic regression models to evaluate:

i. Differences in pre-buyout characteristics to define a set of KPIs targeted by PE firms and address hypothesis one
ii. KPI development after buyout dependent on group affiliation regarding hypothesis two
iii. Significant influence of operational engineering on KPI and profitability growth in PE-backed transactions to answer hypothesis three

Following the approach of COHN *et al.* (2021), I will set up multiple models controlling for specific characteristics

[95] See Rosenbaum and Rubin (1985, p. 33).
[96] See Cohn et al. (2022, pp. 265-266).

that might influence FSLIs.[97] Supplementing the approach to determine PSs, I will take fixed effects into account by controlling for industry, target home country, and firm age at buyout.

COHN *et al.* also state that there are two main reasons for post-buyout performance in LBOs: either due to unlocking growth opportunities by injecting capital or by distressing struggling firms.[98] For this reason, I will calculate 25% performance quartiles (Q) and investigate whether dependencies of operational engineering do in fact drive value creation in companies based in European. I will therefore investigate time persistence of inter-group quartiles between treatment and control group throughout the observation period.

After having carried out logit models and PSM to determine PE target selection patterns, I will use these results to evaluate the post buyout KPI development dependent on PE ownership through another regression setup. To finally determine whether PE ownership significantly influences value creation through operational engineering, I will use a difference in difference (DiD) regression approach where I will use EBITDA and FCF margin as the dependent variables and add additional explanatory variables. Given this setting, I can control for two-way fixed effects and thereby exclude effects on EBITDA and FCF originating from other sources like financial or governance engineering effects. In addition, I will control for country-, year-, industry-, as well as firm-fixed effects. Thereby I can identify the true effect solely attributable to effects arising from operational engineering.

To address the hypotheses derived in chapter 4.1, the results of my analyses will be presented and expounded in the next chapter. To corroborate my results, chapter 4.6 will critically review the findings and perform robustness tests and sensitivity analyses to critically review the analyses performed.

4.5. Results

Before assessing value creation mechanisms, I consider and analyze pre-buyout characteristics and post-buyout development in sections 4.5.1. and 4.5.2., before applying a DiD approach in section 4.5.3. to account for two-way fixed effects to determine the impact of PE ownership solely attributable to operational engineering.

4.5.1. Analysis of Pre-Buyout Characteristics

To address hypothesis one, I will investigate pre-buyout characteristics of PE transactions to develop a framework of a favorable KPI set for PE transactions. To do this, I perform several logistic regression models do determine effects of KPI levels on buyout likelihood. Overall, I construct six regression models. As shown by other authors, the relevance of certain KPIs might differ depending on their relative size when compared to peers.[99] Therefore, I have also included KPI quartile indicators as explanatory variables. Model I only considers EBITDA and FCF quartile assignment. In model II, I assess pre-buyout EBITDA metrics. To expand this approach, I add lnAsset and Sales quartiles as size proxies as well as leverage as explanatory variables in model III. Models IV and V follow an equivalent setup as regressions II and III, using FCF pre-buyout characteristics instead of EBITDA as explanatory variables of interest. Finally, model VI unites the previous ones considering both EBITDA and FCF margin simultaneously. Including both EBITDA and FCF margin quartile variables in one model is not possible due to the data structure resulting in concerns regarding multicollinearity. The logit models' output is displayed in Table 4.

In all cases, the KPIs as explanatory variables are regressed against the treatment dummy variable, equaling one for PE transactions and zero for control group elements. The model output thereby can be interpreted as the change in likelihood of PE engagement given a change in pre-buyout KPIs. The regression equations are presented in models (A2) and (A3), as shown in Appendix 10.

From these analyses performed, it becomes clear that pre-buyout FSLI characteristics do have a significant impact on PE buyout likelihood - as expected. In particular, EBITDA margin and quartiles as well as sales quartiles as a size measure drive these effects: while higher EBITDA quartile assignment increases the buyout likelihood, above-average profitability appears to have the opposite effect. On the other hand, results on FCF impact are more blurred, as can be seen in models IV and V.

Besides this, PE firms seem to target comparably small firms, measured by sales, as the sales quartile coefficient is significantly negative in all cases. The direction and significance of the effects observed does not change when adding additional explanatory variables worthwhile considering like lnAssets and leverage.

To re-evaluate the results, I have additionally controlled for country-, year-, and industry-fixed effects in separate models, yielding the same results as displayed. Also, the coefficient of determination, expressed by Nagelkerke's pseudo R^2,[100] shows sufficiently high levels of explanatory power for most models. Besides the coefficient of determination, I calculate the root mean squared error (RSME) for each model. With the results achieved, I can confirm the findings of coefficient significance and satisfactory explanatory power for the logit models. However, I could not include margin quartile explanatory variables in model VI due to the dataset's structure and coefficient correlation. Moreover, to mitigate possible concerns regarding explanatory power and model reliance due to correlation within the explanatory variables, I calculate a variance inflation factor (VIF) for all explanatory variables in models I to VI.[101] From this analysis, I can preclude potential model deficiencies arising from multicollinearity.

[97] See Cohn et al. (2022, p. 276).
[98] See Cohn et al. (2022, p. 271); Acharya et al. (2009, p. 2).
[99] See Cohn et al. (2022, p. 262, pp. 260-270).
[100] See Nagelkerke (1991, p. 1).
[101] See Johnston, Jones, and Manley (2018, pp. 1958-1959).

Table 4: Logistic Regression Models on Buyout Probability given KPI Levels at Buyout

KPI	**Logistic Regression Models**					
	I	II	III	IV	V	VI
$EBITDA_{T-1}$ Margin		-0.01**	-0.06^{x}			-0.07**
$EBITDA_{T-1}$ Margin Q		-0.06***	-0.02			
$EBITDA_{T-1}$ Q	0.07***	0.07***	0.09**			0.07*
FCF_{T-1} Margin				0.12	-0.06	0.01
FCF_{T-1} Margin Q				0.07*	0.02	
FCF_{T-1} Q	0.00			-0.09**	0.01	0.02
$lnAssets_{T-1}$ Q			-0.01		0.07	-0.02
$Sales_{T-1}$ Q			-0.20***		-0.18***	-0.19***
$Leverage_{T-1}$ Q			0.03		0.04^{x}	0.03
Pseudo R^2	7.26%	16.73%	19.10%	2.99%	15.75%	19.34%
RSME	0.36	0.45	0.49	0.46	0.46	0.45

Logistic regression outputs predicting buyout probability given level of EBITDA and/or FCF indicators at buyout. Logit I addresses the effect of overall EBITDA and FCF size (quartiles), while Logit II covers different EBITDA characteristics, only. Logit III adds lnAssets and sales quartiles as size proxies and leverage to account for financial engineering. Models IV and V are analogue to models II and III, investigating FCF instead of EBITDA. Model VI investigates both EBITDA and FCF while also controlling for further influencing factors. In each regression, the dichotomous Treatment Dummy variable, taking one for PE buyouts and zero for non-PE backed transactions is the dependent variable. The level of significance is represented by an asterix where the explanatory variables are statistically significant at a 0.1% (***), 1% (**), 5% (*), or 10% (^{x}) confidence level.

To sum up, the findings from the logistic regression models do support the indicative findings as well as the descriptive tests carried out in the previous chapters in terms of quartile effect and profitability and size. Therefore, the next section will focus on KPI development post-buyout to set a starting point on value creation through PE ownership.

4.5.2. KPI Development throughout the Observation Period

As in particular quartile explanatory variables showed very high levels of significance, I want to further evaluate the relevance of KPI quartile assignment and quartile differences between treatment and control group.

To do this, I first perform an analysis of variance (ANOVA) on quartile KPI levels, which yields highly significant differences in means between control and performance group quartiles. Thus, I once again apply a t test on means on each quartile bracket of control and treatment group in the pre-buyout year as well as the end of the observation period in T+2, as displayed in Appendix 6. In line with the results obtained in the logit models, the quartile and margin means do differ significantly between treatment and control group both pre- and post-buyout. In most cases, the above-median companies showed higher levels for all KPIs in the control group. This in in line with the results obtained in the previous section: albeit PE firms appear to target companies with relatively high levels of EBITDA, higher relative levels of pre-buyout sales as a size proxy significantly decrease buyout likelihood. As the analyses carried out so far show similar and statistically significant results, I can already address hypothesis one and hypothesis two partially:

> *PE firms target small firms compared to control group transactions. This can be seen by an on average significantly lower sales base. However, these PE targets seem to be less profitable, as can be seen by the regression results for the included profitability quartiles, namely EBITDA margin and margin quartiles.*

As can be seen, the pre-buyout characteristics do differ significantly as PE firms seem to systematically target potential portfolio companies with a predefined set of KPIs. However, I first and foremost want to evaluate whether PE activity also has a positive impact on these KPIs during the holding period.

To further investigate the initial findings on time persistent differences in KPI quartiles, I perform propensity score matching. In this setting, PSM is a very powerful tool as it allows me to analyze similar companies in terms of pre-buyout characteristics and thereby assess the real impact of PE ownership. To do this, I use a comparable model to the ones displayed in Table 4 to calculate the propensity scores for each transaction and match each treatment group observation to one non-PE backed transaction.[102] The initial results of PS distribution in the new dataset generated through PSM support the findings of the logit models already carried out.

Thus, the analyses performed so far show significant impact of pre-buyout KPI levels on the likelihood of PE engagement. Also, I have demonstrated that relative FSLI size

[102] See Acharya et al. (2009, pp. 21-22, p. 42).

in terms of KPI quartile assignment is persistent throughout the observation period. Specifically, relatively low levels of EBITDA (margin), which is one of the favored pre-buyout characteristics for PE backed transactions, provide opportunities for value generation through operational improvements. The findings of persistent KPI quartile assignment differences between treatment and control group firms also indicate that PE firms do create surplus economic value through operational engineering. These implications of operational engineering measures implemented by the PE firm in fact increasing EBITDA and FCF are thus reinforced by the quartile assignment development as shown above. These findings are also in line with other papers. For instance, COHN *et al.* also find evidence for PE firms targeting comparably unprofitable firms, as this allows the highest potential for margin improvement, what the authors refer to as "*turnaround opportunities*".[103]

However, from both, the findings on pre-buyout characteristics as well as the significant differences in quartile assignment throughout the observation period, no causal relationship between operational improvements implemented by the PE firm and KPI enhancement as well as overall higher profitability improvements can yet be drawn. Albeit these findings may suggest a significant relationship, changes in KPIs as well as their underlying FSLIs can just as likely be due to other reasons. For instance, leverage used by the PE firm may lead to more capital readily available in the first periods after buyout that could be used to launch new products or enter new markets and thereby increase sales and thus EBITDA, as interest payments are not incorporated in this figure. While this would be associated to financial engineering, also increased efficiency through improved governance mechanisms may yield higher EBITDA or FCF. However, in the presented analyses, this would spuriously be assigned to operational engineering effects. Therefore, I cannot yet deduce a causal relationship between PE involvement and increasing EBITDA and FCF solely attributable to operational engineering from the results obtained so far.

4.5.3. Difference in Difference Analysis of Private Equity Ownership Effect on Operational Engineering

To establish a causal relationship of whether PE firms make use of operational engineering to increase profitability and thereby generate value, this chapter will use methods capable of determining causal inference.

Besides operational and financial engineering as the two performance driving strategies resulting in a direct bottom-line effect, also time-, industry-, country-, and firm-fixed effects likely pose a relevant factor in KPI development. However, as most of these effects do influence the same KPIs and FSLIs, there are interdependencies between all of them.

To finally address hypothesis three and the overarching topic of this paper, I will decompose the growth effects originating from macroeconomic effects, leverage, and operational improvements. For this reason, I will use a multivariate analysis that can capture two-way fixed effects. The interacting two-way fixed effects, namely the simultaneous influence of pre- and post-buyout characteristics as well treated and untreated item-fixed effects can be analyzed in a difference-in-difference (DiD) setting. By adding lnAssets as a size proxy I can control for firm size effects while leverage as another explanatory variable captures profitability gains through financial engineering. In addition, by including *Fama French* industry factor dummy variables, I can control for industry-wide time-series variation in business conditions.[104] From this, I can genuinely assess the value generation attributable to operational engineering without neglecting effects arising from other sources like financial engineering or firm- and industry specific circumstances. To perform this DiD regression, I first manually transform the cross-sectional dataset retrieved from Orbis and transformed through PSM into a panel data set.

After this final data preparation, I set up two linear regression models, one for EBITDA and FCF margin, contemplating every transaction *i* in every period *t*. The models read as follows:

$$\begin{aligned} EBITDA_{Margin(i,t)} &= \beta_0 + \beta_1 \left(Treatment_{i,t}\right) \\ &+ \beta_2 \left(postbuyout_{i,t}\right) + \beta_3 \left(Treatment \times Post\right) \\ &+ \beta_4 \left(Leverage_{i,t}\right) + \beta_5 \left(lnAssets_{i,t}\right) \\ &+ \beta_6 \left(Industry_{i,t}\right) + \varepsilon_{i,t} \end{aligned} \tag{1}$$

$$\begin{aligned} FCF_{Margin(i,t)} &= \beta_0 + \beta_1 \left(Treatment_{i,t}\right) \\ &+ \beta_2 \left(postbuyout_{i,t}\right) + \beta_3 \left(Treatment \times Post\right) \\ &+ \beta_4 \left(Leverage_{i,t}\right) + \beta_5 \left(lnAssets_{i,t}\right) \\ &+ \beta_6 \left(Industry_{i,t}\right) + \varepsilon_{i,t} \end{aligned} \tag{2}$$

In this setting, the influence of several factors on EBITDA and FCF margin can be assessed simultaneously. Besides the regression's intercept β_0, β_1 as the first DiD component displays the overall PE ownership effect. This entails the pre-buyout period T-1, as the exact date of transactions is not taken into consideration due to data availability. In addition, β_2 indicates the development as of T0 for all transactions and represents the second DiD component - post buyout. Finally, β_3 unites both DiD aspects by adding explanatory power on the effect of PE ownership on value creation, which ultimately is the variable of interest.

In addition, potential influences arising from financial engineering are considered by the regression coefficient β_4. In fact, the post-buyout PE-ownership value creation factor β_3 can describe value creation solely attributable to operational engineering measures. Additionally, lnAssets and *FF* industry classification factor dummy variables are added as covariates, acknowledged with coefficients β_5 and β_6. In an additional model I have controlled for unobserved confounders

[103] Cohn et al. (2022, p. 271).

[104] See Cohn et al. (2022, p. 271).

Table 5: Difference-in-Difference Regression Models - Influence of PE ownership on Profitability through Operational Engineering

KPI	DiD lm Regression Models					
	I	II	III	IV	V	VI
β_1 Treatment	-0.29***	-0.29***	-0.29***	-0.03	-0.09	-0.09
β_2 Post Buyout	-0.28***	-0.26***	-0.27***	-0.26**	-0.25**	-0.25**
β_3 Post Buyout Treatment	0.29***	0.27***	0.28***	0.03	0.05	0.05
β_4 Leverage	0.00***	0.00**	0.00**	0.00	0.00	0.00
β_5 lnAssets		-0.02*	-0.02*		-0.07***	-0.06***
R^2	5.15%	5.41%	5.50%	3.06%	5.46%	5.62%
RSME	0.56	0.56	0.56	0.58	0.57	0.57

DiD Regression with PSM EBITDA and FCF Margin as the dependent variables. DiD model with two-way fixed effects also taking treatment point of time T0 into consideration with parallel observation of influence of explanatory variables on dependent variable as measure for operational engineering quality. Models I to III display output with EBITDA margin as dependent variable, models IV to VI with FCF margin. While models I and IV only include the treatment dummy and leverage to assess the impact of PE ownership and parallel impact of financial engineering through leverage, models II and V also control for firm size using lnAssets as a proxy. Models III and VI also control for *Fama French* industry-fixed effects. The level of significance is represented by an asterix where the explanatory variables are statistically significant at a 0.1% (***), 1% (**), 5% (*), or 10% (^{x}) confidence level.

by including country-, year-, and firm-fixed effects dummy variables, achieving the same overall results.

I start the analysis by only including the two-way fixed effects coefficients β_0 to β_4 in model I for EBITDA margin. The same model with FCF margin as the dependent variable is displayed in model IV. In models II and V, I also include lnAssets as an explanatory variable. To assess the model quality, I add the coefficient of determination, measured with Nagelkerke's pseudo R^2. In addition, I calculate RSME as a second quality measure. To mitigate potential concerns arising from multicollinearity, I calculate VIFs for every coefficient also in this model.[105] The results from the model quality tests are satisfactory. The results of the DiD regression are displayed in Table 5.

For models I to III describing EBITDA margins, one can clearly see a strongly significant decline post buyout for all models. However, the relevant two-way fixed effects coefficient β_3 is strongly significant and positive in all cases. This coefficient will only be positive for PE-backed firms after the buyout has occurred. Interestingly, this effect becomes astonishingly strong when comparing it to the overall post-buyout development, depicted by β_2: the overall post-buyout development of EBITDA margin turns out to have a negative slope. In comparison to the two-ways fixed coefficient, the effect of PE ownership (treatment group) on this KPI's development turns out to be even stronger. I can therefore conclude from this that PE ownership has s significantly positive influence on EBITDA margin improvement post-buyout. Furthermore, this margin improvement is achieved through operational engineering measures. As I control for effects from financial engineering, namely leverage, and size, with lnAssets as a proxy, as covariates as well as year- and industry-fixed effects in a DiD-setting, this effect can thus solely be attributed to operational engineering measures. In fact, leverage does not seem to significantly impact EBITDA margin, just as industry classification.

In addition, adding more explanatory variables in models II and III (and V and VI respectively), does not increase the explanatory power significantly, as can be seen by a stable coefficient of determination. However, the coefficient of determination shows overall rather low levels. For this reason, I add the root mean squared error (RMSE) for all models to evaluate their overall fit. Like the coefficient of determination, the RMSE does not change significantly when adding additional explanatory variables. Therefore, the combination of highly significant regression coefficients with sufficiently low RMSEs represent strong analytical evidence.

In contrast to the findings on EBITDA margin, the models assessing PE impact through operational engineering on FCF margins show comparable results, thus not being as reliable in terms of statistical significance. Only the post buyout coefficient, just as in the EBITDA margin models, turned out to be significantly negative in model IV. While the direction of the post-buyout treatment and two-ways fixed effects coefficient β_3 is the same in models IV to VI, they are smaller in absolute size - and insignificant. However, the initial FCF DiD model IV also does not convey substantial overall explanatory power, as it yields the lowest coefficient of determination of all six models. Also, the leverage effect did not add significant explanatory power in models IV to VI, while firm size showed a comparable impact on FCF margin as in models I to III on EBITDA margin. Unlike in the EBITDA margin models, however, the introduction of additional covariates β_5 as a firm size proxy and β_6 to account for industry-fixed effects

[105] See Johnston et al. (2018, pp. 1958 - 1959).

does add additional explanatory power to the FCF margin models, achieving comparable explanatory power like models I to III. Thus, even though models IV to VI indicating similar trends compared to models I to III, they did not turn out to add explanatory power to post-buyout treatment effects by PE firms through operational engineering for FCF margin improvement.

With the results obtained from these DiD two-way fixed effects models, I can also address hypothesis two and three, after already having answered hypothesis two above in parts. As demonstrated, pre-buyout characteristics between treatment and control group firms do differ significantly. Furthermore, these KPIs do develop not only at a different pace, but also differently when comparing treatment and control group transactions. This could have been seen through persistence in significantly different KPI quartile allocation throughout the observation period. While this addresses hypothesis two, hypothesis three can be answered with the last analysis' findings. In fact, PE-backed firms do show a significantly stronger increase in EBITDA margin as a profitability measure. As this can be found in a DiD-setting, I can assign this improvement to effects that can be traced back to operational engineering improvements implements by PE firms in their respective portfolio companies. Since operational engineering generally is referred to as EBITDA and FCF effects,[106] I have also investigated FCF margin improvements through operational engineering. While the analyses performed are in line with the findings for EBITDA margin improvement, the lack of coefficient significance does not allow me to assume a causal relationship between operational engineering and FCF margin, unlike with EBITDA margin.

As I could successfully address all three research hypotheses developed in section 4.1., the next section will address potential weaknesses of the analyses performed by carrying out tests on robustness and sensitivity analyses. After the data analysis result reconfirmation sections have been concluded, I will put my findings in an academic framework, comparing my results to comparable papers in section 5.1. Chapter 5.2. will also address potential weaknesses of the analyses performed and will critically review the assumptions made before section 5.3. finally summarizes the findings and chapter 5.4. concludes this paper by demonstrating potential avenues for further research.

4.5.4. Model Evaluation: Tests on Robustness and Sensitivity

In the last section, I have demonstrated and elaborated on the impact of PE involvement on statistically significant improvements in profitability. By applying DiD-models and thereby accounting for two-way fixed effects, I can distinctively assign this margin improvement effect to operational engineering measures. However, while the results from the DiD regressions performed do show significant evidence for EBITDA margin improvement post-buyout, the results are not fully unambiguous given the results regarding FCF margin improvement as well as the coefficients of determination. In view of the lack of verifiably positive impact of PE activity on FCF margin improvement, a commensurable figure to EBITDA margin, the results should be examined more critically. For this reason, I revalidate the model outputs by testing for robustness.[107]

I therefore start by visually inspecting robustness of the models defined in equations (1) and (2) as well as the output. Just as the difference in coefficient significance, the results do differ when comparing EBITDA and FCF margin regression residuals, as displayed in Appendix 13 for models I to III and Appendix 14 for models IV to VI: EBITDA margin shows a sufficiently homogeneous distribution of fitted and residual regression coefficients as well as fit to theoretical vs. actual regression quartiles to test for heteroskedasticity and normality. Similarly, I investigate overall data distribution: EBITDA margin residuals show a right skewed and strongly leptokurtic distribution. In contrast, however, FCF margin regression residuals display a left-skewed residual distribution while also showing some evidence for homoskedasticity and non-normally distributed residuals, which, however, is in line with the findings retrieved through DiD regressions IV to VI.

As the results of visually inspecting the propensity score matched data regression outputs and performing analyses on robustness, I finally want to reaffirm the results by conducting a sensitivity analysis through model variation tests. To do this, I apply a commonly used approach to reducing the present PSM sample to sub-groups.[108] I do this in two steps: first apply the DiD regression model on the dataset while excluding one country per model. As another superordinate model, I control for sensitivity by buyout year. In addition, I control for firm-fixed effects. The regression results for country and industry level sensitivity analyses are displayed in Appendices 15 and 16. As well as the visual inspection as tests on robustness, the sensitivity analyses do confirm the overall significant impact of PE ownership on EBITDA margin improvement post-buyout and thereby operational engineering as a highly relevant value creation driver in PE transactions.

5. Discussion

Having presented the analyses results in the previous sections, I will now summarize and discuss my findings. I start by putting my results in a framework of the current academic discourse. Subsequently, I will discuss my results in chapter 5.1. and compare them to other authors findings on PE value creation through operational engineering. From this, I will draw a conclusion and assess the implications of my results. Thereafter, I will critically review my results and section 5.2. and discuss potential weaknesses of the models applied and analyses presented. I will sum up this paper with concluding remarks in chapter 5.3., before finally showing possible

[106] See, for instance, Achleitner et al. (2010, p. 19); Achleitner et al. (2011, pp. 2-3).

[107] See Lu and White (2014, p. 1).

[108] See Salciccioli, Crutain, Komorowski, and Marshall (1973, pp. 265-267).

avenues for further research derived from my work and the academic discourse.

5.1. Implications of the Results Achieved

In this paper, I have analyzed the effect of private equity ownership on value creation through operational engineering. I provide evidence on pre-buyout characteristics in terms of PE firm target selection as well as KPI improvements after buyout through operational engineering. I have applied logistic regression models to determine buyout likelihood given a set of relevant KPIs. From this analysis I can conclude the following buyout characteristics favored by PE firms as

reflected in my sample: in comparison to the control group transactions, PE firms target small firms measured by sales. The targeted companies are comparably unprofitable regarding EBITDA margin. I have reaffirmed these characteristics by determining the KPI quartiles and their development throughout the observation period, finding statistically significant and time persistent differences between treatment and control group.

Following the pre-buyout characteristics, I have demonstrated the relevance of operational engineering activities for value creation in PE transactions. I have shown this by applying propensity score matching and thereby comparing extraordinarily similar companies. By using a DiD approach, I have controlled for two-way fixed effects of year- and industry-fixed effects as well as interdependencies resulting from financial engineering on the KPIs to be evaluated. From this analysis, I can conclude that PE firms are particularly effective in applying operational engineering activities to increase profitability. The results achieved keep their overall explanatory power when testing for model robustness by adding additional explanatory variables and have been reaffirmed by performing sensitivity analyses.

As extensively highlighted in the introductory sections, operational engineering represents, amongst financial and governance engineering, one major driver in value creation in PE transactions. Following the mathematical decomposition introduced by Achleitner *et al.* with the value creation bridge, EBITDA and FCF effect can be described as the main drivers yielding surplus value created through operational engineering.[109] Since value creation through operational engineering can also be perceived as the metrics attained through actual measures and skillful implementation of successful actions by the PE firm, I have focused on these KPIs within my European deal-level data set.

In line with COHN *et al.*, who state to be the first to determine PE target characteristics and predict favorable KPI sets of companies PE firms acquire, I have performed comparable analyses on my dataset.[110] I also find a significantly negative impact of relative size, measured by sales quartiles, on buyout likelihood. While I find the tendency of PE firms to target comparably unprofitable firms, the authors postulate a U-shaped relationship with higher buyout likelihood for both extrema of (un-)profitability. While I cannot fully reconcile these findings with my dataset, I can partially support this statement as EBITDA margin has a significantly negative impact on buyout likelihood, while higher EBITDA quartile assignment has significantly positive impact on buyout probability.

COHN *et al.* also elaborated on two distinctive theories on why PE firms may be attracted by highly (un-)profitable companies: they either target highly profitable firms because of *"untapped growth opportunities because of financial constraints"*[111] or unprofitable firms as these companies could serve as a growth platform with extraordinarily large optimization opportunities to capitalize on.[112]

This also found by Achleitner *et al.*, stating that high profitability pre-buyout is not associated with larger margin improvements during the holding period.[113] With the data collected from Orbis, I can only find evidence on comparably unprofitable target companies in terms of EBITDA margin, supporting the hypothesis of PE firms aiming at the acquisition of companies where they fully use their knowledge and capabilities to increase margins in low-performing firms to capitalize on, which is also what Stafford finds for his dataset. In addition, he also finds evidence on PE firms targeting small firms.[114] Besides size, the academic findings on relevance of leverage on buyout likelihood are inconclusive. While some authors postulate evidence on the relevance of leverage and its decrease during the holding period,[115] Stafford and other authors, just as I, find no evidence on leverage being a highly relevant KPI predicting buyout likelihood.[116] However, as Stafford uses public-to-private transactions, the mean firm size in the dataset likely is larger and thus PE transactions might appear to be relatively small in comparison to the other transactions included in his dataset. Nevertheless, this might also be the case for my dataset - this could be assumed given the significantly higher mean sales volume for control group transactions.

On the other hand, however, Acharya *et al.* cannot confirm these findings as they find evidence of the selection pattern being non-linear in profitability, thus PE firms targeting companies that are neither unprofitable nor highly profitable.[117] My results achieved through PSM partially support this view, as well, as displayed in the margin PS distribution displayed in Appendix 11.

Comparing the results presented by Cohn *et al.* and Acharya *et al.*, I would classify my results as a finding at the intercept of both papers: while I cannot find evidence for PE firms targeting firms with above-average EBITDA margins, as found by Cohn *et al.*, this does not necessarily imply that the

[109] See Achleitner et al. (2010, p. 19).
[110] See Cohn et al. (2022, p. 260).
[111] Cohn et al. (2022, p. 271).
[112] See Cohn et al. (2022, pp. 268-270).
[113] See Achleitner et al. (2011, p. 14).
[114] See Stafford (2015, p. 12).
[115] See Achleitner et al. (2010, p. 5).
[116] See Stafford (2015, p. 11).
[117] See Acharya et al. (2009, p. 5).

margins are negative, as can also be seen by the KPI quartile means calculated. This supports the view of Acharya *et al.*, who also postulate that PE firms target companies with high upside, but low downside potential. This pattern could also explain the results achieved in my logit models and can, as discussed, be explained by the high due diligence efforts usually entailed in PE transactions.[118]

As the analysis on pre-buyout KPI characteristics and the derivation of a KPI level set favored by PE investors has been carried out successfully, I have further followed the approach of Cohn *et al.* and Acharya *et al.* by performing PSM to create dataset of treatment and control group transactions which are highly similar in pre-buyout KPI characteristics. Analogue to these contributions, I perform more advanced statistical analyses on the propensity score matched dataset to assess the impact of PE involvement on post-buyout KPI development. In fact, my finding of increased profitability in PE-backed transactions after buyout, as unveiled through DiD two-way fixed effects regression, has also been found by Cohn *et al.*: their result of PE involvement significantly increasing profitability for propensity score matched peers, which is even stronger the lower the profitability pre-buyout, can also replicated with my dataset and analysis.[119] I was able to demonstrate that companies with low levels of EBITDA margin pre-buyout for PE targets grow significantly stronger by operational engineering measures. Thereby I can convey the same testimony as Cohn *et al.* have by stating that PE firms also target firms with lower profitability as they are capable *"to turn around struggling firms"*.[120]

Thus, as a preliminary conclusion, I can summarize that PE firms use a defined set of pre-buyout KPIs for potential portfolio companies and, unlike non-PE backed firms with extremely similar FSLI characteristics, significantly increase profitability. They do this by operational engineering, primarily addressing EBITDA and thus the main drivers for operational engineering.[121]

The results of Cohn *et al.* as well as mine are also in line with the results of Acharya *et al.* on operational improvements. This paper also shows evidence on gains in profitability through operational improvements for PE-backed transactions. In fact, my results of overall margin improvement versus post-buyout PE impact on EBITDA margin as demonstrated in the DiD regressions can also be compared to the analysis performed by Acharya *et al.*: while I could not find evidence on EBITDA margin gains for the overall PSM dataset, PE engagement showed a highly positive and significant impact post-buyout. Also, with the analyses and additional tests and taking two-way fixed effects into account, I can assign these gains in EBITDA margin improvements to operational engineering.[122] What's even more, my findings of PSM increasing the positive impact of PE ownership on above-average profitability improvements, in comparison to the overall dataset, is what Cohn *et al.* could also find.[123]

Besides the concurrence of this papers' findings with existing literature applying PSM, Hahn also found significant impact of PE ownership on value creation through operational engineering in a DiD setting comparable to mine. In fact, he also found a significant post-buyout treatment effect on EBITDA margin growth resulting in abnormal performance due to the relevant KPIs *"being causally altered by PE ownership"*.[124]

By taking two-way fixed effects into consideration when assessing the relevance of operational engineering, I have also considered the relevance of leverage, thus financial engineering, on buyout likelihood. The development throughout the observation period and results from the analyses performed suggest lower relevance of financial engineering on value creation. This is also what Cohn *et al.* found in more thorough investigations.[125] Even though I could not confirm findings on FCF effect with my dataset, I could prove the relevance of EBITDA effect as the primary driver of value engineering operational engineering.[126] Overall, the findings presented in this paper are in line with the prevailing sentiment in academic discourse.[127]

5.2. Potential Weaknesses and Shortcomings

So far, I have covered the strengths of my analyses and have put their implications in the context of other author's contributions. Albeit having conducted tests on robustness and sensitivity analyses, I also want to address potential weaknesses of my analyses and areas of interest not covered in this paper before presenting potential avenues for further research starting points in the last chapter.

First and foremost, in line with academic consensus, I have decided to investigate an observation period of four years in this paper, three of which after buyout (including the buyout year). While collecting the data from the Orbis Bureau van Dijk database, I have only included transactions where I was able to retrieve all relevant KPIs for the entire observation period. These detrimental KPIs are, EBITDA, assets, the FSLIs to calculate FCF according to the definitions displayed in Appendix 1, and leverage. While an average holding period of around four years for PE investments in Europe seems plausible,[128] this may have led to low levels of selection bias as I most likely have excluded several transactions where not every KPI was available for every single year

[118] See Puche (2016, p. 41)
[119] Cohn et al. (2022, pp. 272-273).
[120] Cohn et al. (2022, p. 270).
[121] See Achleitner et al. (2010, p. 19).
[122] See Acharya et al. (2009, p. 12, pp. 24-25).
[123] See Cohn et al. (2022, p. 258).
[124] Hahn (2009, pp. 27-28, p. 43).
[125] See Cohn et al. (2022, p. 283).
[126] According to most academic contributions, EBITDA effect appears to be the most relevant value creation driver within the operational engineering strategy. See, for instance, Puche (2016, pp. 40-42).
[127] See Achleitner et al. (2010, pp. 25-26); Achleitner et al. (2011, pp. 14-15); Biesinger et al. (2020, pp. 28-19); Graf et al. (2009, pp. 25-26); Guo et al. (2009, p. 28); Kaplan and Strömberg (2009, pp. 132-133, p. 143); Puche (2016, p. 41).
[128] See Achleitner et al. (2010, p. 25).

- for instance, I have excluded eleven Swiss control group transactions as my preconditions led to all Swiss treatment group transaction being dropped. Also, besides the figures I classified as detrimental for my analyses, data availability was poor for several KPIs. For this reason, I was not able to calculate EV for a sufficiently large subset of treatment and control group transactions. Therefore, I could not translate the findings on the positive impact of PE ownership on profitability into the influence of operational engineering on EV/EBITDA multiple, a widely used multiple in the sphere of private transactions, and thereby quantify the actual value created.

As seen from the first analyses in section 4.2., both treatment and control group transactions do significantly differ in their pre-buyout characteristics. This difference may lead to overt bias, which could occur when, already before treatment, the treated and control group differ in their characteristics. Indeed, I am aware of statistically significant differences between the groups to be compared but nonetheless carry out the analyses. However, by applying PSM, the negative influence of overt bias can sufficiently be reduced as I have applied k nearest neighbor matching as an algorithm reducing overall distance of propensity scores and thereby only taking very similar transactions into consideration for further evaluation.[129] This matching method also is well suited to wipe out potential biases arising from the control group being significantly larger than the treatment group.[130] Therefore, PSM through k nearest neighbor matching is a suitable method to achieve reliable causal inference in my dataset.[131]

After carrying out analyses on probability of PE involvement based on pre-buyout FSLI characteristics, I have carried out DiD regression models to assess the impact of PE ownership on operational engineering. As discussed in the previous section, my findings of PE ownership resulting in significantly higher EBITDA margin improvements is in line with other author's findings. This setup is capable of assessing the implications of operational engineering, while accounting for two-way fixed effects, namely hidden effects of financial engineering and year-as well as industry-fixed effects. In addition, I have also controlled for country-, year-, and firm-fixed effects through the sensitivity analyses. Also, using a linear regression model as standard method that is widely used is favorable as other methods in R entail very specific prerequisites and are not necessarily similarly well suited for my analyses.

While the statistical methods applied to analyze the data at hand were proven to be suitable, the output might in parts provide reasons for doubt. In line with Cohn *et al.* and Acharya *et al.*, amongst others, I find evidence on profitability gains through operational engineering.[132] As postulated and mathematically decomposed by Achleitner *et al.*, EBITDA and FCF are the main operational engineering value creation drivers. While I found strong and consistent evidence on improvements in profitability measured by EBITDA margin, this was not the case for FCF margin. The post-buyout effect of PE ownership on FCF margin was positive, nevertheless not significant in my models. Also, I could not find evidence for FCF margin improvement as a relevant source of value creation through operational engineering. What is interesting is the fact that when examining buyout probabilities, the impact of FCF margin pre-buyout appeared to have statistically insignificant thus opposing effects on probability of PE involvement.

To reaffirm the results obtained, I have performed additional tests to assess their significance. Overall, the tests on robustness confirm the relevance of EBITDA as a highly relevant performance driver in value creation through operational engineering. However, just as in the DiD models, I could not find genuine evidence for FCF margin improvement.

Besides tests on robustness and sensitivity analyses, I have mainly assessed model quality by interpreting the coefficient of determination. Given their values being rather low in the DiD setting, I critically reviewed my analyses. However, when comparing my results to the ones of Acharya *et al.*, my results appear to be comparably good and thus sufficiently strong in explanatory power, as they find coefficients of determination between 6% and 16%.[133] In addition, I have calculated RSME as additional model quality assessment and VIF to mitigate concerns regarding variable correlation.

5.3. Conclusion

In this paper, I have investigated value creation mechanisms through operational engineering, the driver gaining more and more relevance for PE firms to create excess economic value in last decades.[134] In line with recent literature, I have focused on deal-level data of Europe-based target firms, following and uniting approaches presented in recent academic contributions in my analyses.[135] With the analyses performed and put in an academic framework, I conclude my findings by addressing the research hypotheses developed in section 4.1. as follows:

a. PE firms have a distinct selection pattern. They target firms with comparably low levels of sales volume that are unprofitable measured by EBITDA margin. Also, high levels of leverage do not have a significant impact on buyout probability.
b. PE-backed firms do significantly increase profitability (measured by EBITDA margin). The margin improvement is significantly stronger in PE-backed transactions and time persistent throughout the observation period.

[129] See Rosenbaum (2010, pp. 74-75).
[130] See Ferman (2021, p. 1).
[131] See Stuart (2010, p. 9-10).
[132] See Acharya et al. (2009, p. 24).
[133] See Acharya et al. (2009, p. 41).
[134] See, for instance, Achleitner et al. (2010, pp. 17-18); Harris et al. (2013, p. 20).
[135] See Acharya et al. (2009, pp. 14-22); Cohn et al. (2022, pp. 262-264); Hahn (2009, pp. 42-44).

c. With the analyses performed, I can demonstrate a significant increase in EBITDA margin solely attributable to operational engineering as a prevailing driver of value creation in PE transactions. My findings are in line with academia mainly stating that operational engineering is the primary driver of value creation in recent transactions, especially in Europe.

By considering two-way fixed effects and thereby disentangling simultaneous effects on KPIs, I could reaffirm target selection patterns and KPI development throughout the observation period. By applying PSM, I could create a dataset of extremely similar matched transactions which, unlike the overall dataset, did not show any significant differences in FSLIs. Through this, I was able to add additional explanatory power to all models performed. Even when using this dataset where treatment and control group transactions are mutually exclusive as well as collectively exhaustive, I demonstrated significant EBITDA margin improvements post-buyout for PE-backed transactions. By adding a two-ways fixed effects coefficient also controlling for buyout year as well as lnAssets and sales as a size proxy to control for size-fixed effects and leverage to take returns from, i.e., tax shield effects into account, I can decisively define EBITDA effects as a result of operational engineering measures employed by the PE firm, as suggested by Achleitner *et al.*, amongst others.[136] To also consider country-, industry-, year, and firm-fixed effects, I have performed tests on robustness and sensitivity, which reaffirm my overall results.

So far, most existing literature has focused on US and UK based transactions on fund-level data.[137] However, as the European market appears to show different characteristics in value creation, I followed the approach of other authors by applying existent findings and methods to the second largest geographic region for PE transactions: I analyzed European G7 country-based target firm transactions, amended by GSA countries. In addition to the existing approaches on value creation in academia, I have combined two research streams. I use the pioneering approach of applying PSM in a PE setting, like Cohn *et al*. and Acharya *et al*., and apply DiD regressions on this dataset, as suggested by Hahn.[138] To the best of my knowledge, this is the first paper combining these hitherto often overlooked approaches.

My results shed light on margin improvements through operational engineering as a result of PE ownership. They reconfirm existing findings on value creation and combine the benefits of comparing similar PE and non-PE transactions while controlling for two-way fixed effects for transactions in Western Europe. With these results, I can find the same implications of value creation strategies applied by PE firms as other authors. This also means that PE firms do create actual value through their actions. Their impact on margin improvements as examined in this paper is significantly stronger than for non-PE backed transactions. Therefore, I cannot affirm claims such as PE firms not creating value but only transferring wealth through complex compensation schemes (see value transfer hypothesis) and high costs with the only goal of PE firms aiming at realizing swift profits for themselves.[139]

5.4. Avenues for Further Research

While this paper has provided additional evidence on value creation through operational engineering by combining novel approaches, not all relevant factors were in scope and could be covered in the course of this work. For this reason, I want to conclude this paper by presenting interesting opportunities for future work in the sphere of LBOs in general and PE value creation in particular.

First and foremost, data availability did not allow me to calculate EV. For this reason, augmenting my dataset by adding transactions from other commercial databases probably allows doing this and therefore would be worthwhile considering. With an expanded data set, one could translate the impact of operational engineering on overall returns to the GP and even LP to determine, for instance, whether higher EBITDA improvements in PE transactions are reflected in multiple valuation after buyout. Thus, a joint consideration of KPI and multiple development (e.g., EBITDA/EV multiple) would be a promising approach for further research.

While several authors find strong evidence on the relevance of FCF in value creation, my analyses could not find a significant relationship. Therefore, extending this work by further investigation on FCF margin improvement might be useful, too. Also, more in-depth work on pre-buyout characteristics to add more evidence on the selection pattern regarding profitability, given the diverging findings in this special aspect of Cohn *et al.* and Acharya *et al.* and my results, that share characteristics of both analyses, could be interesting.[140]

Given the powerful tool of PSM, more research using this approach is desirable. While academic contributions on PE value creation for European transactions has significantly increased in the last decade, the overall understanding of value creation mechanisms in this market is not yet as mature as it is in the US. Therefore, more thorough investigations of the development of value creation mechanisms as well as their implications on overall returns in comparison to Anglo-American transactions using new approaches is an interesting track to follow. Besides this, also a focus on Eastern European transactions could be interesting, as there are barely any academic contributions on these market dynamics, so far.[141] Similarly, only few authors studied value creation and

[136] See Achleitner et al. (2010, p. 9).

[137] This can be seen by the differing value-driving mechanisms. See, for instance, Achleitner et al. (2011, p. 17, pp. 25-26).

[138] See Acharya et al. (2009, pp. 14-22); Cohn et al. (2022, pp. 262-264); Hahn (2009, pp. 42-44).

[139] See Stafford (2015, pp. 26-30); Anders (1992, pp. 8-12); Lowenstein (1985, p.731).

[140] See Acharya et al. (2009, pp. 22-25); Cohn et al. (2022, p. 269, pp. 274-277).

[141] For one academic contribution on value creation through operational engineering see Rikato (2014, pp. 22-45).

selection patterns in PE transactions for Asia-Pacific.[142] Thus, comparative analysis of these markets with geographies like Europe and North America, where the PE industry appears to be more mature, likely is insightful, as well.

It will be interesting to see how the volumes of LBO transactions will change in the years to come with higher macroeconomic uncertainty and rising interest rates and inflation globally. As leverage was particularly high in the last years due to the low interest rates and credit spread,[143] this might change in the next years. In fact, the availability of inexpensive debt will likely decrease which will have an impact on the entire PE market.[144] Thus, another shift from the booming PE industry into other asset classes might reinforce the cyclicality of PE as an alternative asset class. Also, as prices for PE investments were at an all-time high in recent years, institutional investor may reallocate investments for publicly traded securities or other asset classes.

Overall, it remains to be seen whether the current macroeconomic situation has set an end to the buyout boom in recent years.[145] The last buyout waves shifted the relevance of value creation mechanisms from financial to operational engineering. It nevertheless remains to be seen whether new macroeconomic conditions still offer sufficient opportunities to employ these strategies. Considering global developments, it is conceivable that the well-established mechanisms of PE target selection patterns and value creation strategies will alter - whether it will be governance engineering or indeed completely new value driving factors to be employed remains to be seen altogether. The next years will most likely impressively show whether overall returns and value creation strategies have become more resilient and if PE target firm selection patterns adapt to the new situation.

[142] For a comparative analysis of PE value creation in Europe and Asia see Puche (2016, pp. 22-73).

[143] See Acharya et al. (2007, p. 9).

[144] See Achleitner et al. (2010, p. 17).

[145] See PricewaterhouseCoopers GmbH Wirtschaftsprüfungsgesellschaft (2020, pp. 18-21).

References

Acharya, V. V., Franks, J., & Servaes, H. (2007). Private Equity: Boom and Bust? *Journal of Applied Corporate Finance*, *19*(4).

Acharya, V. V., Hahn, M., & Kehoe, C. (2009). Private Equity Target Selection: Performance and Risk Measurement based on Propensity Score Matching. *Working Paper*.

Achleitner, A.-K., & Braun, R. (2015). *Handbuch Entrepreneurship. Entrepreneurial Finance. TUM School of Management* (G. Faltin, Ed.). Wiesbaden, Springer Gabler.

Achleitner, A.-K., Braun, R., & Engel, N. (2011). Value creation and pricing in buyouts: Empirical evidence from Europe and North America. *Review of Financial Economics*, *20*(4), 146–161.

Achleitner, A.-K., Braun, R., Engel, N., Figge, C., & Tappeiner, F. (2010). Value Creation Drivers in Private Equity Buyouts: Empirical Evidence from Europe. *The Journal of Private Equity*, 17–27.

Anders, G. (1992). *The "Barbarians" in the Boardroom. Harvard Business Review.* https://hbr.org/1992/07/the-barbarians-in-the-boardroom.

Asness, C. S., Krail, R., & Liew, J. M. (2001). *Do Hedge Funds Hedge? AQR Capital Management LLC.* https://ssrn.com/abstract=252810.

Axelson, U., Jenkinson, T., Strömberg, P., & Weisbach, M. (2012). Borrow Cheap, Buy High? The Determinants of Leverage and Pricing in Buyouts. *Forthcoming Journal of Finance*.

Axelson, U., Jenkinson, T., Weisbach, M. S., & Strömberg, P. J. (2008). Leverage and Pricing in Buyouts: An Empirical Analysis. *Working Paper*.

Berg, A., & Gottschlag, O. (2003). Understanding Value Generation in Buyouts. *Journal of Restructuring Finance*, *2*(1), 9–37.

Beuselinck, C., Elfers, F., Gassen, J., & Pierk, J. (2021). Private firm accounting: the European reporting environment, data and research perspectives. *Accounting and Business Research*, 1–45.

Biesinger, M., Bircan, Ç., & Ljungqvist, A. (2020). Value Creation in Private Equity: EBRD Working Paper No. 242. *Swedish House of Finance Research Paper*, *20*(17).

Braun, R., Jenkinson, T., & Schemmerl, C. (2016). Adverse Selection and the Performance of Private Equity Co-Investments. *SSRN Journal*.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Lawrence Erlbaum Associates.

Cohn, J. B., Hotchkiss, E. S., & Towery, E. M. (2022). Sources of Value Creation in Private Equity Buyouts of Private Firms. *Review of Finance*, *26*(2), 257–285.

Dalgraad, P. (2008). *Introductory Statistics with R*. Springer New York.

Engel, N., Braun, R., & Achleitner, A.-K. (2012). Leverage and performance of buyouts: (How) does the use of debt Impact equity returns? *Zeitschrift für Betriebswirtschaft*, *82*, 451–490.

European Commission. (2022). *Exchange Rate (InforEuro).* https://ec.europa.eu/info/funding-tenders/procedures-guidelines-tenders/information-contractors-and-beneficiaries/exchange-rate-inforeuro_en. (Accessed: 22.09.2022)

Fang, L., Ivashina, V., & Lerner, J. (2015). The disintermediation of financial markets: Direct investing in private equity. *Journal of Financial Economics*, *116*(1), 160–178.

Ferman, B. (2021). Matching estimators with few treated and many control observations. *Journal of Econometrics*, *225*(2), 295–307.

French, K. R. (n.d.). *Detail for 5 Industry Portfolios.* https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_5_ind_port.html. (Accessed: 28.09.2022)

Gompers, P., Mukharlyamov, S., & Mukharlyamov, V. (2015). What Private Equity Investors Think They Do for the Companies They Buy. *Harvard Business Review*.

Graf, C., Kaserer, C., & Schmidt, D. (2009). Private Equity in Financial Institutions: Value Creation and Performance. *SSRN Journal*.

Guo, S., Hotchkiss, E. S., & Song, W. (2009). Do Buyouts (Still) Create Value? *Journal of Finance, Forthcoming*.

Hahn, M. (2009). *Essays on Private Equity Value Creation: Financial and Operating Performance in Private Equity Owned Companies* (Dissertation). Ludwig-Maximilians-Universität München.

Harris, R., Jenkinson, T., & Kaplan, S. (2013). *Private Equity Performance: What Do We Know?* Cambridge, MA.

Heckman, J. J. (1979). Sample Selection Bias as a Specification Error. *Econometrica*, *47*(1), 153.

Jensen, M. C. (1986). Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers. *The American Economic Review*, *76*(2), 323–329.

Johan, S., & Zhang, M. (2021). Information Asymmetries in Private Equity: Reporting Frequency, Endowments, and Governance. *Journal of Business Ethics*, *174*(1), 199–220.

Johnston, R., Jones, K., & Manley, D. (2018). Confounding and collinearity in regression analysis: a cautionary tale and an alternative procedure, illustrated by studies of British voting behaviour. *Quality & quantity*, *52*(4), 1957–1976.

JPMorgan. (2021). Food Fight: An update on private equity performance vs public equity markets.

Kaplan, S. (1989a). The Effects of Management Buyouts on Operating Performance and Value. *Journal of Financial Economics*, *24*.

Kaplan, S. (1989b). Management Buyouts: Evidence on Taxes as a Source of Value. *The Journal of Finance*, *44*(3), 611–632.

Kaplan, S., & Strömberg, P. (2009). Leveraged Buyouts and Private Equity. *Journal of Economic Perspectives*, *23*(1), 121–146.

Kaplan, S. N., & Schoar, A. (2005). Private Equity Performance: Returns, Persistence, and Capital Flows. *The Journal of Finance*, *60*(4), 1791–1823.

Knitterscheidt, K., & Murphy, M. (2020). *Der Notverkauf - Thyssen-Krupp verkauft Aufzugssparte für 17 Milliarden Euro: Thyssen-Krupp verkauft seine Aufzugssparte am Finanzinvestoren. Mit der Abgabe des letzten verbleibenden Gewinnbringers will der Konzern sich retten. Handelsblatt.* https://www.handelsblatt.com/unternehmen/industrie/elevator-geht-an-investoren-der-notverkauf-thyssen-krupp-verkauft-aufzugsparte-fuer-17-milliarden-euro/25587478.html. (Accessed: 19.09.2022)

Levene, H. H. (1960). Robust tests for equality in variances. In I. Olkin & H. Hotelling (Eds.), *Contributions to Probability and Statistics: Essay in Honor of Harold Hotelling* (pp. 278–292). Stanford University Press.

Ljungqvist, A., Richardson, M., & Wolfenzon, D. (2008). The Investment Behavior of Buyout Funds: Theory and Evidence. *Cambridge, MA*.

Lowenstein, L. (1985). Management Buyouts. *Columbia Law Review*, *85*(4), 730–784.

Lu, X., & White, H. (2014). Robustness checks and robustness tests in applied economics. *Journal of Econometrics*, *178*, 194–206.

Nagelkerke, N. J. D. (1991). A note on a general definition of the coefficient of determination. *BIOMETRIKA*, *78*(3), 691–692.

Phalippou, L., & Zollo, M. (2005). What Drives Private Equity Fund Performance? *Working Paper*.

PricewaterhouseCoopers GmbH Wirtschaftsprüfungsgesellschaft. (2020). Private Equity Trend Report 2020 - Bull or bear? *With the support of Steve Roberts and Elena Naydenova*.

Puche, B. (2016). *Essays on Value Creation and its Determinants in Private Equity* (Unpublished doctoral dissertation). Technische Universität München, München. TUM School of Management.

Rikato, M. (2014). *Essays on Private Equity: Operating Performance, Investment Selection Success and Costliness of Placement Agents* (Unpublished doctoral dissertation). University of Ljubljana, Ljubljana. Faculty of Economics.

Rosenbaum, P. R. (2010). *Observational Studies* (2nd ed.). Springer.

Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score. *The American Statistician*, *39*(1), 33–38.

Salciccioli, J. D., Crutain, Y., Komorowski, M., & Marshall, D. C. (1973). Sensitivity Analysis and Model Validation. In P. Zarembka (Ed.), *Frontiers in econometrics* (pp. 263–271). New York.

Sender, H. (2013). *Lunch with the FT: David rubenstein. the co-founder of the carlyle group is worth an estimated $3bn. over lobster bisque, he talks about his plans to give away the bulk of his fortune. financial times.* https://www.ft.com/content/97a35d8c-90ac-11e2-a456-00144feabdc0. (Accessed: 09.11.2022)

Sensoy, B. A., Wang, Y., & Weisbach, M. S. (2014). Limited partner performance and the maturing of the private equity industry. *Journal of Financial Economics*, *112*(3), 320–343.

Shapiro, S. S., & Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). *BIOMETRIKA*, *52*(3-4), 591–611.

Stafford, E. (2015). Replicating Private Equity with Value Investing, Homemade Leverage, and Hold-to-Maturity Accounting. *SSRN Journal*.

Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical science: a review journal of the Institute of Mathematical Statistics*, *25*(1), 1–21.
Student. (1908). The Probable Error of a Mean. *BIOMETRIKA*, *6*(1), 1–25.
Wickham, H. (2014). Tidy Data. *Journal of Statistical Software*, *59*(10), 103–138.