PRIVATE EQUITY TRASH? OR TREASURE?

INVESTIGATING OPERATIONAL PERFORMANCE OF SECONDARY BUYOUTS IN SCANDINAVIA

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Abstract

This thesis investigates the operational value creation in secondary buyouts (SBOs) compared to primary buyouts (PBOs) in Scandinavian private equity. The research scrutinizes a dataset of 250 SBOs and PBOs, with an further in-depth examination of the 103 SBOs. The time window of measurement spans from one year prior to two years after the buyout.

The methodological approach involves direct extraction and hard coding of financial data based on consolidated financial statements. This data approach enhances the quality and credibility of findings. Statistical testing is done by employing OLS-regression.

The findings underscore divergent strategies in value-creation plans. While PBOs demonstrate more growth, SBOs extend profitability and return measures, revealing a recurring trade-off pattern between growth and profitability/margins. Despite this pattern, the study's findings lack statistical significance, making the differences in performance in the buyout types indistinguishable from zero, challenging pre-existing assumptions.

Investigating drivers that enhance SBO operating performance did not yield conclusive results. Nevertheless, the study does highlight fund specialization within a specific industry as the most statistically significant and consistent factor impacting SBO performance. SBOs acquired under pressure performed better than their counterparts, although the timing distribution related to these pressure investments suggest favorable market conditions may be a contributing factor to these unexpected results. Other potential drivers such as CEO replacement, pressure investing, and complementary skills between lead partners lacked statistical significance.

These findings challenge traditional perspectives by revealing no statistical difference in the overall performance between SBOs and PBOs. The results underscore the importance of understanding the specific factors that influence operational value creation and caution against biases. This study contributes to both academic and professional fields by presenting new data on the performance differences and influencing factors between secondary- and primary buyouts.

Contents

Abbreviations

AOP - Abnormal operating performance

AuM - Assets under Management

BLUE - Best Linear Unbiased Estimator

CAGR - Compounded Annual Growth Rate

Capex - Capital Expenditure

CEO - Chief Executive Officer

EBIT - Earnings Before Interest and Tax

EBITDA - Earnings Before Interest, Tax, Depreciation, and Amortization

EV - Enterprise Value

FA - Fixed Assets

FCF - Free Cash Flow

FF10 - Fama & French industry classification

GP - General Partner

IC - Invested Capital

IFRS - International Financial Reporting Standards

i.i.d. - Independent and Identically Distributed

IRR - Internal Rate of Return

KPI - Key Performance Indicator

LBO - Leveraged Buyout

Ln - Natural Logarithm

LP - Limited Partner

M&A - Mergers & Acquisitions

MBO - Management Buyout

ME - Margin Expansion

NACE - Nomenclature of Economic Activities

NIBD - Net Interest-Bearing Debt

Nopat - Net Operating Profit After Tax

NWC - Net Working Capital

OLS - Ordinary Least Squares Regression

PBO - Primary Buyout

PE - Private Equity

R&D - Research & Development

ROA - Return on Assets

ROE - Return on Equity

ROIC - Return on Invested Capital

RQ - Research Question

SBO - Secondary Buyout

SIC - Standard Industrial Classification

VC - Venture Capital

VCP - Value Creation Plan

WACC - Weighted Average Cost of Capital

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1.0 Introduction

In the realm of private equity, one can distinguish between various types of buyouts, including public-to-private transactions, management buyouts, and secondary buyouts (McKinsey, 2023). Specifically, a secondary buyout refers to the sale of a company previously owned by a private equity firm to another private equity firm. Such a transaction inherently presupposes the occurrence of an initial buyout. Consequently, tertiary, quaternary, and subsequent buyouts also fall under secondary buyouts.
Secondary buyouts (SBOs) are now a major part of the private equity (PE) industry. Their rise in recent decades has drawn interest from those within the industry, investors, and researchers. SBOs have attracted increased interest as they offer dual benefits: an efficient exit channel for private equity firms looking to divest their holdings and, simultaneously, an investment channel for PE firms seeking to deploy capital. S. Kaplan and Strömberg (2009) show a rise in SBOs from 5% between 1979 and 1984 to 31% after the financial crisis in 2008 globally. This suggests that SBOs are used more to manage portfolios and make trading strategies more efficient. Still, there are doubts about whether SBOs can generate value, especially when the first buyer has used all available methods to maximize value before selling.

> *Under the hypothesis that the first private equity investor has been effective in mitigating agency problems by implementing enhanced governance practices, engaging in active management monitoring, and reducing free cash flow, it is unclear how a second, back-to-back financial sponsor can contribute to creating value by exploiting these same mechanisms.* (Bonini, 2015)

Investigating SBOs can provide valuable information and improve understanding of the private equity industry and how value is created in these transactions. Specifically, an SBO happens when one private equity firm sells a portfolio company to another. This is different from the usual leveraged buyout, where a private equity firm buys a company from its original shareholders or takes a public company private. The idea that an SBO can achieve the expected return, especially when the first ownership period has used all operational and financial strategies, may seem challenging to understand.

The figure below showcases the number of buyouts in Denmark, Norway, and Sweden since 2005, divided into PBOs and SBOs. The share of either type of buyout is relatively dispersed during the period. However, SBOs capture a significant deal volume throughout the period.

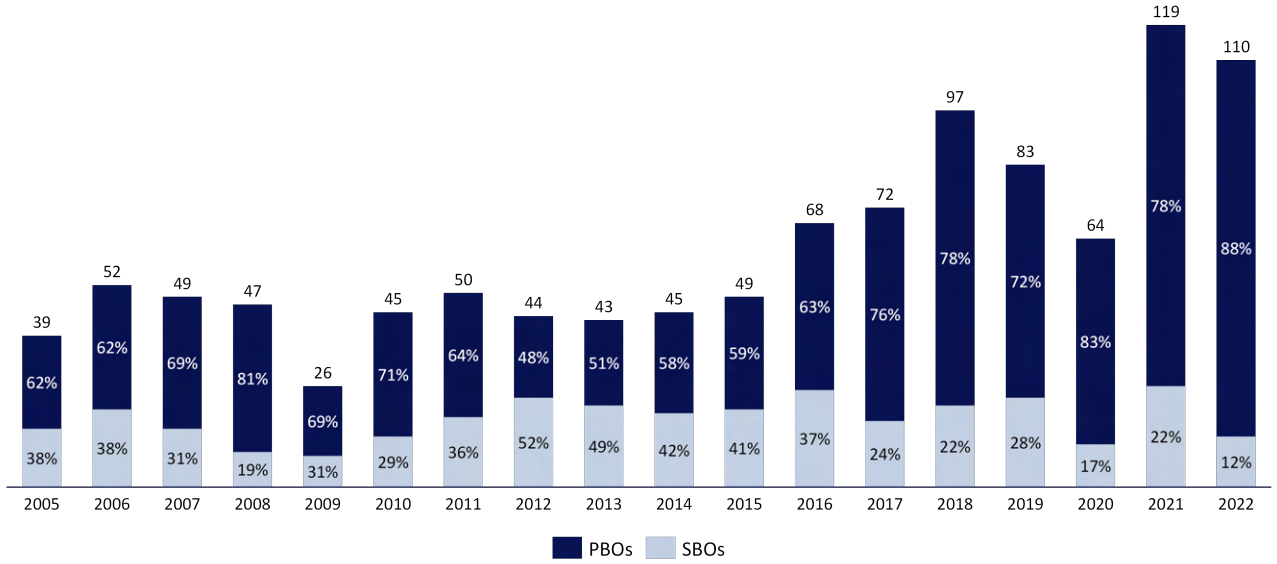


Figure 1.1: Buyouts by type in Denmark, Sweden, and Norway

Source: Preqin, Authors creation

The growing prevalence of SBOs in the Scandinavian private equity arena piques interest for several reasons. Firstly, SBOs may serve as an alternative exit route for PE firms seeking to divest holdings more efficiently, particularly in challenging market conditions (Arcot et al., 2013; Jenkinson & Sousa, 2015; Plagborg-Møller & Holm, 2017). By providing a mechanism for liquidity and capital recycling, SBOs enable PE firms to maintain their investment pace and facilitate continuous capital deployment. Secondly, SBOs offer an avenue for value creation that extends beyond the traditional methods deployed in primary buyouts (PBOs). An SBO buyer can possess industry knowledge and operational expertise. Hence it may be better positioned to unlock latent value in the target company. This can lead to improved performance and returns for investors, making SBOs an attractive investment proposition (Degeorge et al., 2015; Wang, 2012). However, a key concern surrounding SBOs is the ability to generate operational value creation, mainly when the first buyer has already utilized all available tools to maximize value. Critics argue that the low-hanging fruit[1] for operational improvements may have already been reaped down during the PBO, leaving limited space for the new PE owner to add value (Arcot et al., 2013). This raises questions about the true value-creation potential of SBOs and the likelihood of achieving superior returns to investors.

Research on SBOs may enhance academic scholarship by identifying factors influencing financial performance and elucidating the risks and rewards of SBO transactions. Such knowledge proves invaluable for private equity firms, investors, and other stakeholders aiming to optimize their investment strategies. It aids in navigating the intricate task of asset allocation within the SBO market of private equity investing, all while addressing potential issues surrounding operational value creation.

In recent years, private equity has outperformed other alternative asset classes and has demonstrated its ability to generate strong returns even during challenging economic conditions (McKinsey, 2023). The Danish Council for Return Expectations projects that private equity will provide the highest expected returns among all asset

[1]Low-hanging fruit is an expression for easy or plausible ways to enhance company value

classes in the forthcoming decade (Danish Council for Return Expectations, 2023). Given the growing share of SBOs and the potential for strong returns in private equity, the authors are motivated to explore the topic of SBOs in greater depth. Examining operational performance in secondary buyouts opens a fascinating window into a market segment of increasing importance and rapid evolution within the private equity industry. Delving into the intricacies of SBOs can shed light on the underlying motivations, value creation opportunities, risks, and limitations associated with these transactions, ultimately benefiting investors, industry practitioners, and academics alike.

1.1 Motivation of Research

This paper is motivated by ambiguous findings in the existing literature. Various scholars have researched the phenomenon of inferior operational value creation in SBOs relative to PBOs. While some argue that SBOs are subject to inferior operational performance compared to PBOs, others find no significant evidence of inferior operational performance. Most existing literature employs selected metrics, such as growth, profitability, return, efficiency, and debt, to gauge operational value creation. Yet, when analyzing the determinants driving operational value creation, the current body of literature fails to yield consistent conclusions (Achleitner et al., 2014; Bergström et al., 2007; Bonini, 2015; Degeorge et al., 2015; Wang, 2012). It is important to emphasize that this study does not aim to analyze investor returns. Instead, it is focused on assessing operational value creation in SBOs through financial statement analysis. Initially, the thesis investigates whether the operational performance of SBOs in Scandinavia is inferior to that of PBOs. Subsequently, the thesis explores the prediction of superior performance by assessing potential drivers that could enhance operational value creation.

1.2 Research Questions

Given the introduction, it is compelling to study operational value creation in private equity, specifically through financial statement disclosures. This thesis will address the following two research questions.

Research Question 1

Do secondary buyouts exhibit inferior operational performance compared to primary buyouts?

Research Question 2

Which factors in the private equity toolbox are drivers of operational value creation in secondary buyouts?

The first question addresses the issue of inferior operational performance in SBOs relative to primary buyouts. The second research question investigates drivers of operational value creation and their impact on financial KPIs. These drivers represent initiatives private equity firms can apply to enhance operational performance. The private equity toolbox will be elaborated on in chapter three.

1.3 Delimitations

The research area for this project is extensive, and the available data is limited, which necessitates certain constraints. This section will discuss the main delimitations that have been deliberately chosen, keeping the specific research questions in mind. The PE sector tends to be secretive, with undisclosed transaction values that are, at best, questionable. This presents the first limitation of the thesis: given that transaction values

of PE deals are rarely disclosed, the focus of this paper will not be on investor returns but on the operational performance of portfolio companies. It is hypothesized that investor returns are reflected in improvements in the operational performance of the portfolio company, thereby serving as a proxy for investor returns. This concept can be linked to the conventional method of measuring value - the Discounted Cash Flow (DCF) model. This model posits that only factors contributing to future cash flows affect the company's value (Koller et al., 2020). The principle that future free cash flow is the only determinant of a company's value can be illustrated as follows.

$$\lim_{k\to\infty} \frac{E_t(P_{t+k})}{(1+R)^k} = 0 \tag{1.1}$$

Thus, the value converges to

$$P_t = \sum_{i=1}^{\infty} \left(\frac{1}{1+R}\right)^i E_t(D_{t+i}) \tag{1.2}$$

where:

P = price of the stock or asset

D = dividend or cash flow of the asset

R = discount rate

The fundamental principle of the formula implies that as the holding period of an asset approaches infinity, its present value ultimately converges to zero. Therefore, the asset's intrinsic value is derived from all future accumulated discounted cash flows or dividends, adjusted to reflect their present value (Linton, 2019). This underpins the rationale for using performance measures from financial statements as proxies for value creation. These proxies reflect the underlying value of the asset, in this case, the portfolio company.

This paper aims to present a sample of buyouts that accurately embody the features of traditional PE buyouts and ownership. To maintain the results' reliability and validity, certain transactions that could potentially distort the confidence in the results have been excluded. For example, minority investments were removed since PE firms usually acquire majority stakes to fully implement value-creation plans (VCPs). The data sample was also carefully refined to exclude venture capital firms and management buyouts. This exclusion ensures that the sample only includes buyouts reflecting the characteristics of traditional private equity buyouts and ownership. In the context of this thesis, Scandinavia encompasses Denmark, Sweden, and Norway. This classification is based on the linguistic similarities among these countries, facilitating a more effective interpretation of financial statements. It is important to note that Finland is excluded from this categorization due to its distinct accounting practices. In Finland, private companies have the option to adopt either IFRS[2] or FAS[3] (Azets, 2023). As a result of these variations in accounting practices, the inclusion of Finland in the Scandinavia grouping could introduce potential complexities and nuances that may not align with the scope of this thesis. Therefore, the focus is specifically on Denmark, Sweden, and Norway in this thesis.

[2]International Financial Reporting Standards
[3]Finnish Accounting Standards

1.4 Thesis Design

The design of this thesis utilizes a funnel-like structure to provide a comprehensive framework, ensuring that the thesis can stand alone and offer readers a holistic understanding of the PE industry. It begins with a broad introduction that elucidates the motivations and rationale for pursuing further research in this domain. The paper then delves deeper into the complexities of PE, highlighting the conceptual framework of PE. Furthermore, it investigates the value creation mechanisms implemented by PE funds, thoroughly examining the private equity toolbox. Subsequently, the paper presents a comprehensive review of prior literature, progressively narrowing its focus to specifically emphasize existing research on SBOs to familiarize the reader with both consensus and disparities in the existing literature. This exploration of well-established areas in previous literature facilitates the identification of research gaps and intriguing avenues for future inquiry, which will contribute to the formulation of hypotheses. With hypotheses firmly established, the paper presents the methodological scope, taking into account data collection strategies. This naturally transitions to the analysis and interpretation of results, ultimately allowing for subsequent discussion and reflection on the validity and reliability of these analyses. The paper concludes with a systematic summary and identification of the drivers that address each hypothesis, effectively connecting the dots and answering the research questions

Figure 1.2: Thesis Design

2.0 Exploring the Fundamentals of Private Equity

The following sections delve into the conceptual framework of PE. They acquaint the reader with the general characteristics of PE funds and their investment cycle. Additionally, these sections provide an overview of the historical development of the PE industry in the Nordic region.

2.1 Introducing Private Equity

Private equity is an alternative asset class, principally characterized by direct investments for majority stakes in private companies. This implies that PE firms do not invest in listed companies unless they acquire a majority stake allowing a delisting of the public company. PE firms generally focus on acquiring mature companies that exhibit stable earnings and positive free cash flow, as they are obliged to divest portfolio companies within a predefined time frame to repay investors' committed capital, including their returns (Bennedsen et al., 2008). PE funds, being closed-end investment vehicles, have a limited time window for fundraising. Capital is committed by limited partners (LPs), LPs comprise a consortium of investors, primarily institutional investors such as pension funds, insurance companies, banks, asset management firms, family offices, and high-net-worth individuals. General partners (GPs) - synonymous with the PE fund are tasked with selecting target companies, negotiating deals, and overseeing the management of portfolio companies. The typical lifecycle of PE funds is displayed in figure 2.1, illustrating the lifecycle of PE funds.

Once the fundraising is completed, GPs typically have 3-5 years to deploy committed capital in selected portfolio companies. A shortage of suitable buyout candidates fulfilling the fund's investment criteria can lead to dry powder. The holding period usually spans 3-7 years. PE funds occasionally co-invest in syndicates that may include other PE firms and institutional investors, such as banks and asset management firms, particularly when the investment size exceeds the fund's mandate (Bennedsen et al., 2008). During the holding period, GPs work closely with portfolio companies applying various tools to implement growth strategies, improve operations and enhance profitability. Towards the end of the fund's lifetime, there is typically an option to extend the holding period. This not only provides flexibility if the development of portfolio investments does not proceed as planned but also ensures sufficient time for potentially maximizing returns (Bennedsen et al., 2008). Finally, the fund gradually divests its portfolio of companies to realize and distribute returns to LPs.
Source: (Bennedsen et al., 2008), Authors creation

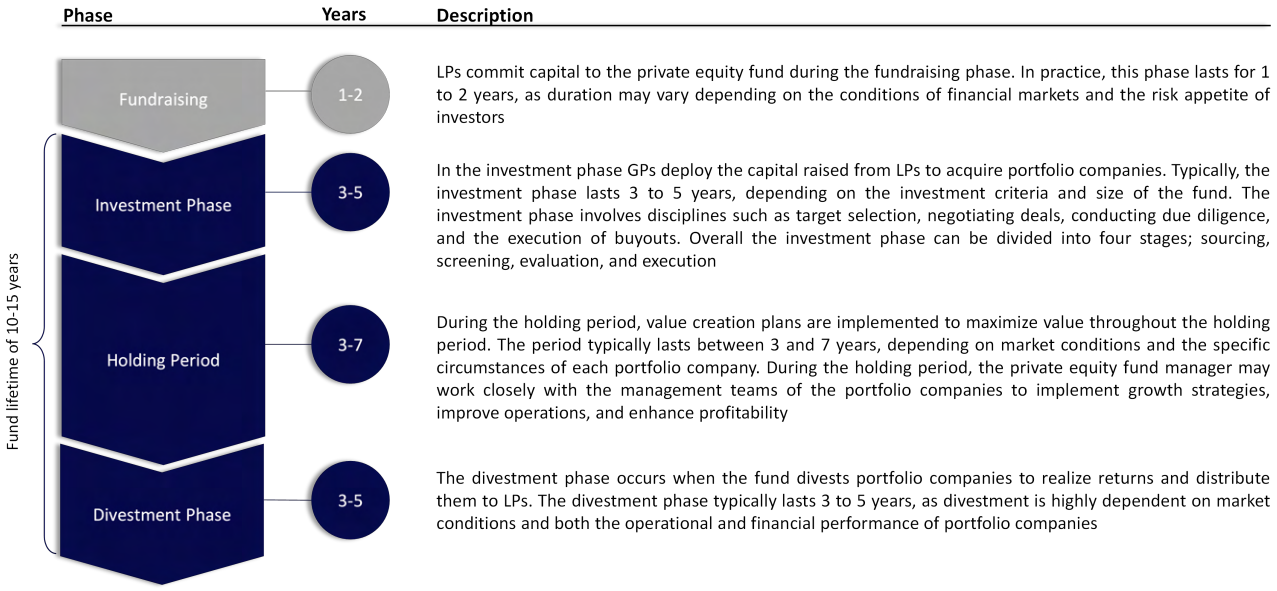


Figure 2.1: Lifecycle of PE funds

2.2 The Organization of PE Funds

PE firms operate as financial and strategic intermediaries between investors and portfolio companies. PE funds engage in various investment activities, including mezzanine debt[1], private placement loans[2], leveraged buyouts, and secondary buyouts. The fund is managed by a management company, itself owned by the executives of the PE firm. Typically, this management company commits between 1 to 5% of the fund's total committed capital (S. Kaplan & Strömberg, 2009). PE funds are usually structured as limited partnerships, wherein the liability of LPs is confined to their committed capital.

GPs can control multiple funds simultaneously. Despite this, each fund operates as an individual entity, maintaining independence even when there is an overlap between GPs and LPs[3]. This autonomy is ensured by assigning a lead partner from the PE fund to each separate investment. A private equity fund operates under specific conditions aligned with the mandate given by the LPs (Bennedsen et al., 2008).

The ownership/holding structure is presented in figure 2.2; the specific fund establishes a holding company (Holding Company I), which receives the capital committed by the LPs and the management company of the PE fund. Subsequently, a Holding Company II is created, into which equity capital from Holding Company I and capital raised through debt financing for the acquisition are injected (Bennedsen et al., 2008). Therefore, items related to the acquisition that appear on the balance sheet are primarily presented as intra-group loans in the financial statements of portfolio companies.

[1] A flexible type of financing that combines elements of debt and equity, typically unsecured, often used by expanding companies
[2] Debt securities issued privately to a selected group of investors, providing quick, cost-efficient financing for small and medium-sized enterprises
[3] GPs and LPs are active in different funds at the same time

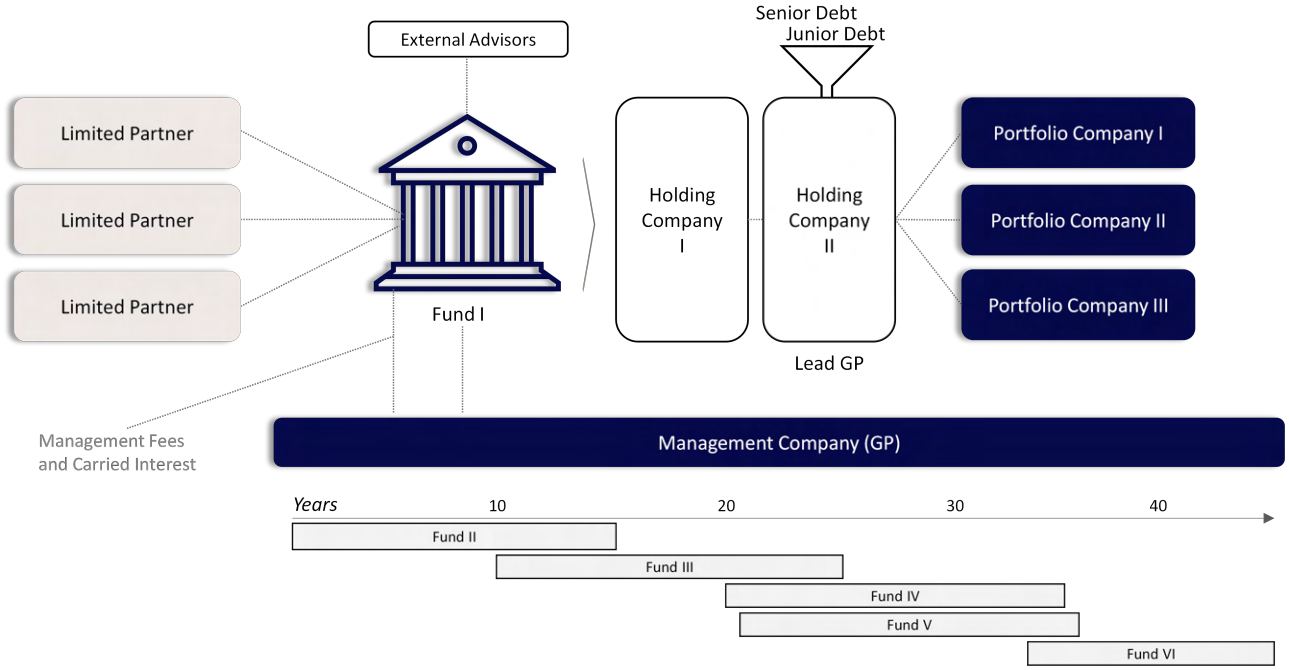


Figure 2.2: Structure of PE funds

Source: (Bennedsen et al., 2008), Authors creation

General Partners (GPs) have four main responsibilities: I) fundraising by pitching the fund to prospective LPs, II) using committed capital to acquire potential target companies, III) actively managing portfolio companies, and IV) divesting investment companies, and redistributing returns to LPs (Stowell, 2018). GPs are compensated in three ways (Gilligan & Wright, 2020). Firstly, GPs receive a 1.5 to 3% annual management fee of the funds committed capital. As investments are realized, this fee shifts to a percentage of capital employed through the investment phase (S. Kaplan & Strömberg, 2009). Secondly, GPs earn 20% of capital profits as carried interest after investors receive a minimum hurdle rate return, usually about 8% (Gilligan & Wright, 2020). Finally, some GPs charge transaction and monitoring fees to portfolio companies to cover employee and partner costs (Gilligan & Wright, 2020).

Limited Partners (LPs) in PE funds typically accept a higher level of risk for a heightened hurdle rate over long investment periods. Returns are not continuous but predominantly distributed when the fund exits its investments, usually via a trade sale or an initial public offering (IPO). Occasionally, some distributions might also originate from the cash flows of the portfolio companies. Investors will receive their share of profits as dividends, provided that the purpose of the cash flow is not to reduce debt (Bennedsen et al., 2008). However, the majority of returns are secured upon successful exits after a period of enhancing the company's value. LPs can influence the decision-making process through advisory boards. The organization of PE funds enables management, in addition to their investment, to have their reputation at stake, which is a significant element in their efforts to secure future capital commitment (Bennedsen et al., 2008).

Banks and Institutional Lenders facilitate debt financing, which is imperative for PE funds in creating superior returns. Banks and institutional lenders facilitate various forms of debt financing depending on the specific transaction. The responsibility of bank consortiums, in collaboration with the investment bank, is to

ascertain the optimal amount of debt the portfolio company can obtain. As a result, banks are frequently involved in the initial stages of acquisitions to guarantee the availability of the required debt financing. The fees and interest banks earn for these services depend on federal interest rates, leverage risk, and the intricacy of the debt package. Usually, PE funds leverage their reputation to secure debt financing on favorable terms (Spliid, 2014).

2.3 Investment Cycle

The investment cycle allows PE funds to allocate capital to portfolio companies, carry out value-creation strategies, and produce appealing returns for LPs. Delving deeper into the complexities of the investment cycle reveals the significance of the investment and divestment stages, ultimately determining the overall performance of PE funds.

2.3.1 Investment Criteria and Deal Origination

Investment criteria and deal origination are fundamental components of the PE investment cycle, as they facilitate funds' ability to identify and select portfolio companies. The fund's mandate includes these investment criteria, guiding its deal-sourcing efforts. Implementing stringent investment criteria, GPs can heighten the probability of identifying portfolio companies aligning with their strategic goals, potentially resulting in substantial returns for their investors (Bennedsen et al., 2008). Investment criteria typically cover the following topics:

- Deal structure, i.e., leveraged buyouts, secondary buyouts, growth capital, or distressed capital
- Target size. Measured by sales, profitability measures, or market share
- Specialization: Possibly focus on a specific industry or sector
- Geography of portfolio companies
- Environmental focus
- Management team
- Growth potential

The investment criteria lay the groundwork for a fund's deal origination, a process that involves the strategic identification and selection of potential target companies; this activity is called deal sourcing. According to Gilligan and Wright (2020), a fund's access to an extensive pool of prospective deals, known as deal flow, is positively correlated with its reputation and past performance. While investment banks and other intermediaries can facilitate sourcing deals, funds typically utilize their unique expertise and rely on additional resources such as professional networks and consultants to efficiently originate deals (Stowell, 2018).

The target selection process necessitates due diligence on potential investments. This comprehensive evaluation, conducted jointly by the fund and external advisors, seeks to ascertain the strategic and financial compatibility of the prospective companies (Rosenbaum & Pearl, 2009). As GPs are responsible for selecting portfolio companies, their mandate is guided by the investment criteria. The literature on LBOs presents some distinct characteristics of companies making them strong buyout candidates for PE funds. The characteristics are inspired by the framework of Bennedsen et al. (2008) and Rosenbaum and Pearl (2009). Characteristics of the

strong buyout candidate can be grouped into two main categories: Financial attributes and Strategic and Operational attributes, depicted in figure 2.3 below. The figure further displays three characteristics highlighted as less important in modern PE.

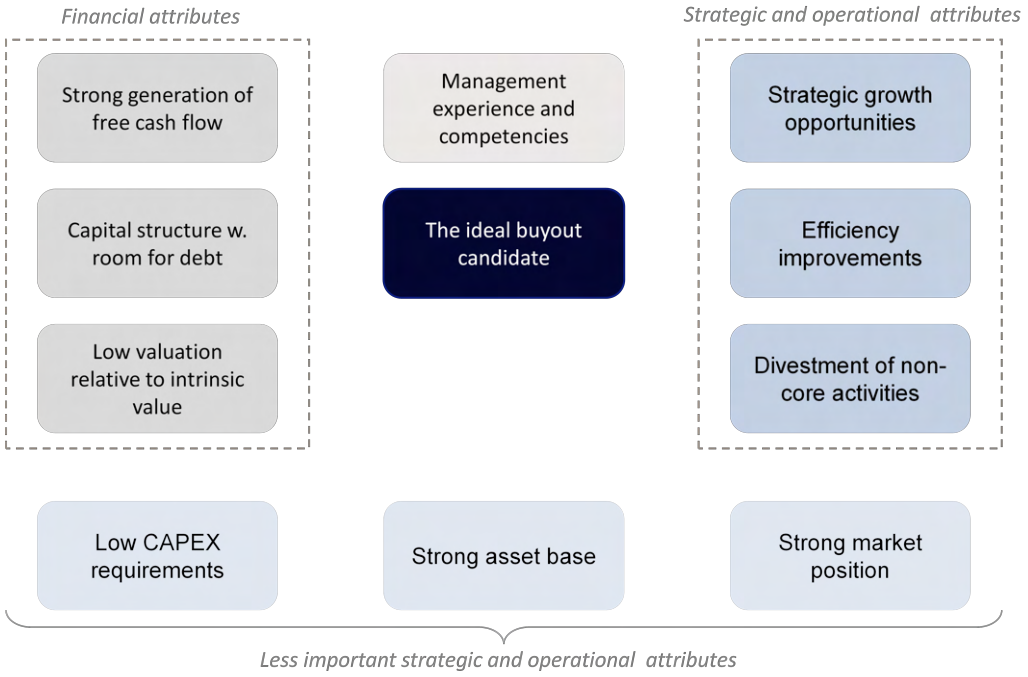


Figure 2.3: Characteristics of the strong buyout candidate

Source: (Bennedsen et al., 2008; Rosenbaum & Pearl, 2009), Authors creation

Let's delve into each characteristic presented in the figure

Financial Attributes

Firstly, a strong buyout candidate should generate a strong and predictable free cash flow. This is paramount to meet periodic interest payments, debt repayment over time, and reinvestment in growth strategies, all of which aid in securing the lowest possible cost of debt. Secondly, the company's capital structure should allow for increased financing, as PE funds typically seek to add more debt to the capital structure. Thirdly, the candidate should have a low valuation relative to its intrinsic value. This attribute is crucial because purchasing at inflated prices during a market peak can significantly diminish the profit potential. On the other hand, acquiring at a low valuation, ideally lower than the company's intrinsic value, provides a more viable pathway for generating robust returns to LPs. This profitability strategy hinges on the PE fund's aim to augment the value of the portfolio company prior to an exit.

Strategic and Operational Attributes

A proven and experienced management team is key in managing a company with a highly-leveraged capital structure. Post-acquisition, PE funds usually retain such teams as they provide confidence in the company's ability to generate cash flow for debt repayment. The strong candidate would also show potential for top-line growth above market levels, driving profitability and generating greater cash flow to support debt repayments. Rosenbaum and Pearl (2009) argue that companies exhibiting strong top-line growth and margin expansion are

more likely to drive an EBITDA valuation multiple expansion. Further, strong candidates present efficiency improvement opportunities. PE sponsors often apply traditional cost-cutting measures to enhance profitability and may explore opportunities to restructure or renegotiate contractual agreements to improve margins.

There seems to be a consensus in the literature that the three attributes highlighted at the bottom have become less relevant during the 2010s (Stowell, 2018). An example is the opportunity to divest non-core entities, as conglomerate companies can often achieve higher separate valuations (Berk & DeMarzo, 2020). A strong asset base and low CAPEX requirements were additional desirable characteristics. A strong asset base has historically been used as collateral for debt financing, and low CAPEX requirements positively impact free cash flow, especially in capital-intensive industries. Lastly, a robust business model that sustains high growth, margin improvements, and a maintainable market position is attractive to PE funds. According to Rosenbaum and Pearl (2009), the focus has shifted towards business models generating superior returns to peers, whereas the market position was an important factor beforehand (Rosenbaum & Pearl, 2009).

2.3.2 Exit Strategies

Overall, the divestment of portfolio companies depends on performance, market conditions, and inherent expectations. PE firms might maintain portfolio holdings for extended periods if the performance does not meet targeted benchmarks (Rosenbaum & Pearl, 2009). The exit is primarily achieved through a sale to a competitor, another strategic bidder/trade sale, or a financial sponsor in the case of an SBO. An important distinction between financial and strategic bidders lies in their ability to realize operating and financial synergies. Direct, quantifiable synergies allow strategic bidders to offer a higher deal value (Gilligan & Wright, 2020). Alternatively, PE funds can choose a partial exit through an IPO, progressively selling shares to public market participants. Generally, the IPO route does not yield an immediate monetization of the portfolio company's equity value. This is because when a PE-owned company undergoes an IPO, it is typically accompanied by an announcement that the PE firm will not exit entirely at the IPO (Rosenbaum & Pearl, 2009). This mechanism fosters investor confidence, as the IPO requires buy-side investors to purchase shares at the offering.

Strong equity market conditions and general economic growth are positively associated with IPOs (Plagborg-Møller & Holm, 2017). However, the IPO route can be time-consuming due to legal requirements. The preparation for an IPO, on average, takes 1-2 years, suggesting that an exit through a trade sale or a sale to a financial sponsor could be a faster exit channel (Berk & DeMarzo, 2020). To support a high exit valuation, PE funds strive to enhance the target's growth and profitability and reduce debt, which in turn increases the equity value of the portfolio company (Rosenbaum & Pearl, 2009). Examining the three most popular exit channels in the Nordics, as visualized in figure 2.4, it becomes evident that SBOs emerge as the second most frequent exit route in the Nordic region, following trade sales.

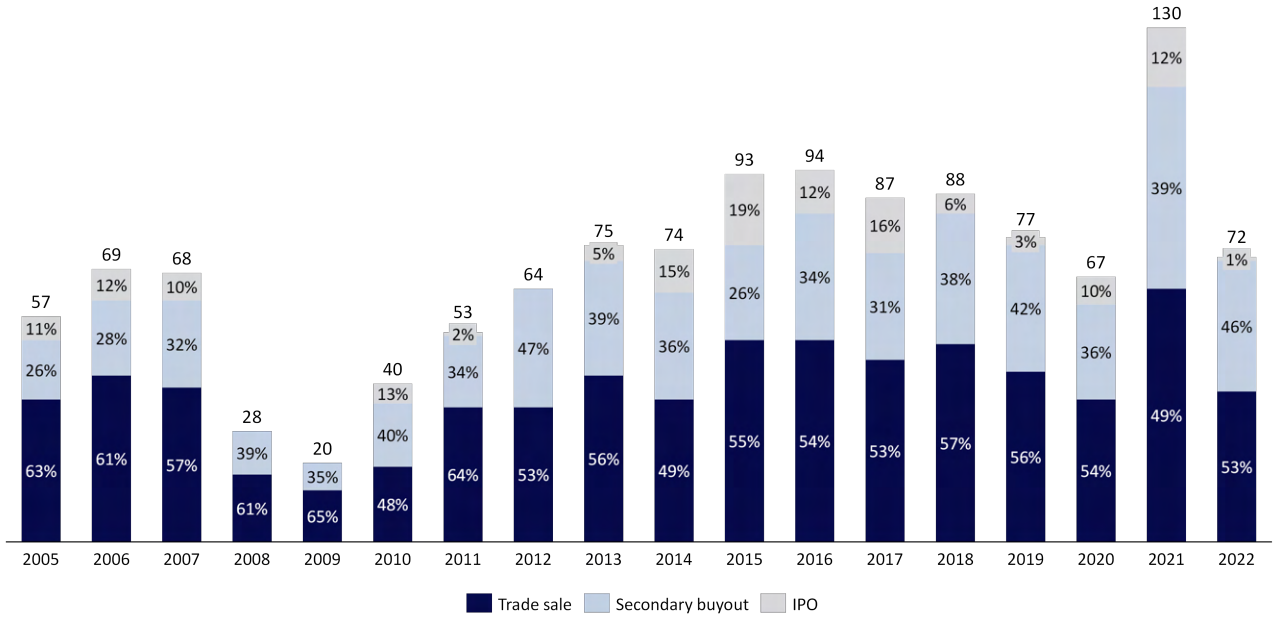


Figure 2.4: Exits by Type in the Scandinavia

Source: Preqin, Authors creation

The data suggest that 2021 was a highly active year for exits in the Nordics. Exit volume declined around the 2008 financial crisis but increased steadily until 2016. The data support the strong equity market conditions and economic growth correlates with increased IPO volume (Plagborg-Møller & Holm, 2017). This correlation is highlighted by the higher occurrence of IPOs in years such as 2017 and 2021, characterized by stronger economic climates. Intriguingly, the proportion of SBOs has seen a noticeable rise in recent years. This trend could signal an increased availability of dry powder in the Nordic PE sector. Alternatively, it might indicate a hesitancy among strategic buyers to engage in acquisitions, possibly due to market uncertainties or perceived high valuations. Moreover, the high level of exits in 2021 aligns with Plagborg-Møller and Holm's finding that a PE fund's decision to pitch a portfolio company for sale may suggest that the selling PE fund anticipates worsening market conditions in the near future (Plagborg-Møller & Holm, 2017). This could potentially explain the high exit volume witnessed in 2021.

2.4 Private Equity in the Nordics

The PE industry has evolved massively in the Nordics. This is emphasized by developing PE assets under management (AuM), which can be decomposed into dry powder and unrealized value. The development of AuM is displayed in figure 2.5.

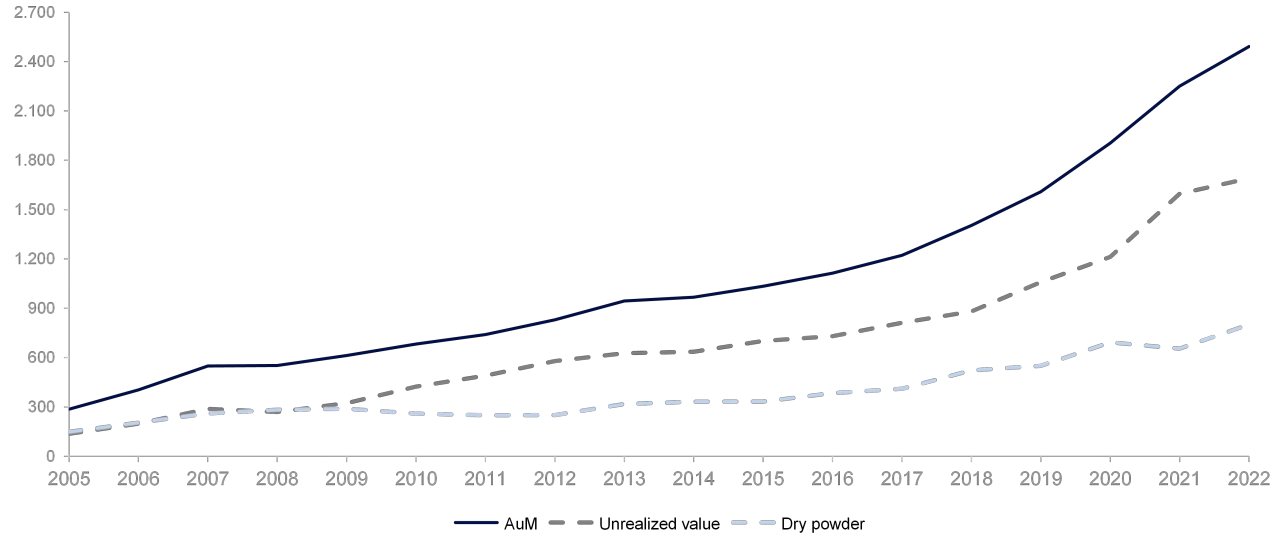


Figure 2.5: Decomposing AuM in Nordic PE

Source: Preqin, Authors creation

Since 2017, unrealized value has increased by 108%, while dry powder has increased by 95% in the same period. The share of dry powder appears to decrease with market volatility, indicating that PE funds deploy capital when valuations are distressed. Supporting this argument, dry powder decreased after the financial crisis in 2009 and 2010 and again in 2021 following the COVID-19 crisis. Unrealized value tends to grow with favorable economic conditions, naturally, as these conditions correspond to multiple expansions in broader markets. AuM in the Nordic region has increased with a cumulative annual growth rate (CAGR) of 14% since 2005, indicating strong growth in capital committed to PE funds.

To further illustrate the development of the PE industry in the Nordics, data on investments by Nordic PE funds has been collected. The development of investments by Nordic PE funds by deal type is displayed in figure 2.6 below.

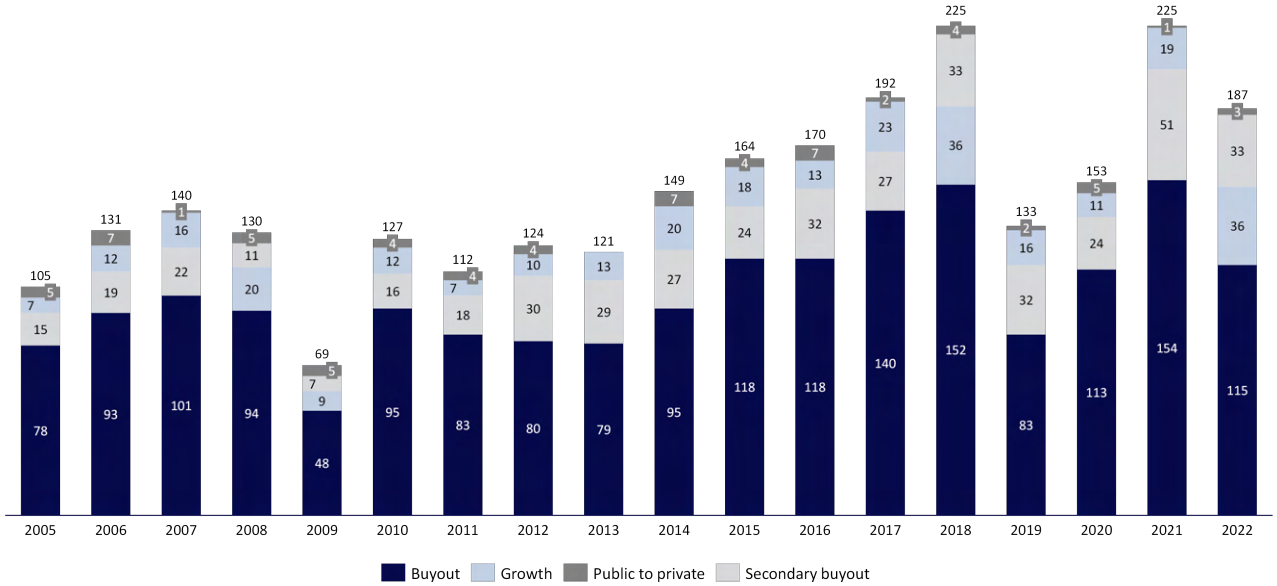


Figure 2.6: PE Investments in Scandinavia by Deal Subtypes

Source: Preqin, Authors creation

The trends in investments by Nordic PE funds underscore that funds capitalize on poor market conditions and distressed valuations. This trend is observable in the investment patterns during 2010 and 2021, both years following significant financial crises, where there was an upsurge in investment volume after an initial slump due to weak market performance. A counter-argument could be made that the increased volumes immediately following economic downturns could be attributed not solely to PE funds exploiting distressed valuations but also to easing monetary policies, which support an increase in investments. Additionally, unspent capital tends to accumulate in funds during economic meltdowns because of a hiatus in buying activity. Consequently, this creates an accelerating incentive to deploy this capital when market conditions stabilize. Furthermore, investment volume appears to decrease two years after these crisis events. Data from the Nordics indicate that SBOs are the second most preferred type of investment, following PBOs, which dominate the observed time series.

Moreover, the distribution of buyouts among the Scandinavian countries is depicted below. It is evident that Sweden holds a dominant position in the buyout market, possibly attributable to the maturity of its financial markets. However, this distribution presents certain challenges in constructing a representative data sample for investigating SBOs in the Scandinavian region.

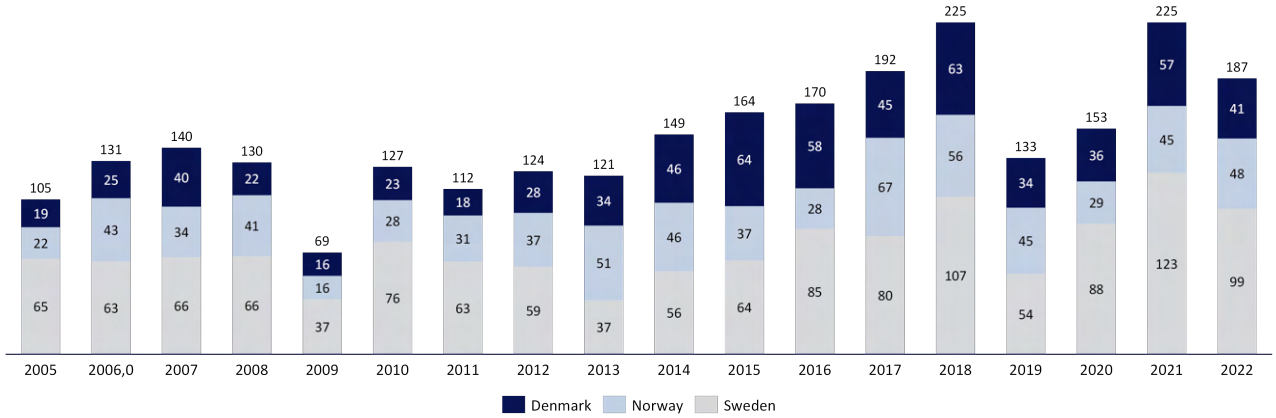


Figure 2.7: Distribution of Buyouts in Scandinavia by Country

Source: Preqin, Authors creation

3.0 The Private Equity Toolbox

This chapter delves into the array of tools employed by PE firms, with particular attention on the drivers of operational value creation. It is akin to peering into a complex toolbox, each tool with a role to play in the broader value-creation process. A comprehensive understanding of these tools forms the foundation for constructing hypotheses and addressing the research questions of this thesis. The focus is on evaluating the operational performance of SBOs. Hence a nuanced understanding of the PE toolbox is crucial. This exploration facilitates a critical evaluation of the strategies and initiatives deployed by PE sponsors.

3.1 Deal Sourcing

The initial step in the PE process, preceding value creation, is deal origination. This stage involves proactive and reactive efforts to identify potential target companies within the investment cycle. Best practices in deal sourcing suggest that when PE funds employ a proactive origination strategy, they tend to achieve consistently higher returns. This outcome is driven by an increased quantity of incoming investment opportunities and their heightened relevance. A proactive origination strategy encompasses building professional relationships with target management teams, generating leads through word of mouth and cold calling, following up on filings and published reports, and attending industry or networking conferences (Teten & Farmer, 2010). As illustrated in figure 3.1 below, the median annual pipeline size required to close one deal stands at 87.

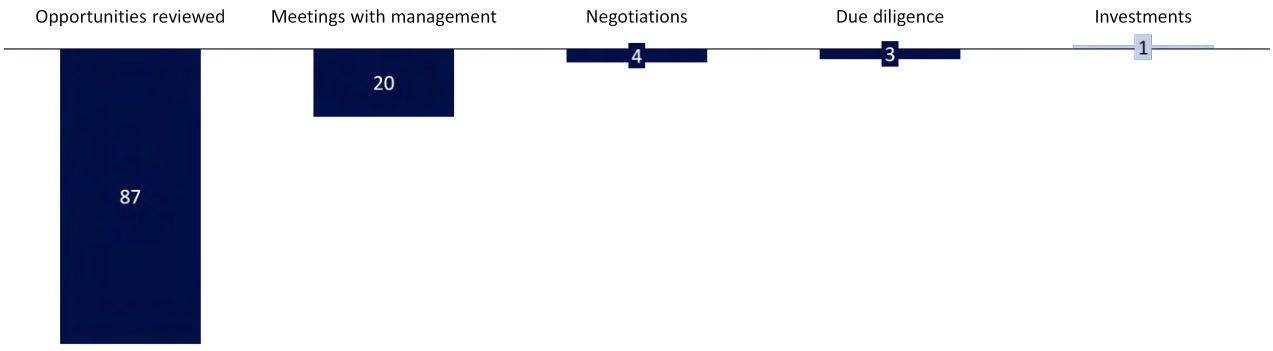


Figure 3.1: The Deal Origination Process

Source: (Teten & Farmer, 2010), Authors creation

Empirical studies suggest that higher returns are typically yielded from investments sourced through personal and professional networks (Teten & Farmer, 2010). This trend is particularly prominent among GPs with more experience, who generally have access to a more attractive deal flow (Gilligan & Wright, 2020). As a common practice, firms devote approximately one-third of their time to target selection (Bennedsen et al., 2008).

3.2 Financial Engineering

Financial engineering encompasses aspects related to capital structure, equity incentives, and alignment of interests. Early research on PE extolled the benefits of financial engineering, contending that the LBO structure outperforms public companies due to the concentration of ownership, which can enhance operational efficiency and overall performance (Jensen, 1989). A central issue identified in public corporations is the phenomenon of empire-building, which arises from a misalignment of incentives between management and shareholders. Specifically, managers may be inclined to undertake negative net present value (NPV) projects to expand the corporation and their scope of authority, but these do not create shareholder value (Jensen, 1989, 1993). The LBO organizational structure, when first identified, was hailed as a game changer by some scholars. They found this structure superior to public corporations, as large debt-service payments compel managers to seek ways to generate cash flow and prevent resource wastage.

Definition 1: Financial Engineering

In this thesis, financial engineering is defined as the strategic process of optimizing a company's capital structure and incentive schemes to harmonize stakeholder interests and mitigate risk. This involves optimizing the balance of equity and debt financing, restructuring existing debt for financial stability, crafting tax-efficient strategies, employing financial derivatives for risk management, and tailoring equity incentives to align managers' and shareholders' objectives, thereby bolstering the company's growth and performance.

The literature presents a consensus in findings that PE firms carefully consider management incentives in target companies, thereby offering the management team a significant equity upside through incentive-based remuneration (Jensen, 1989; S. Kaplan, 1989). Commonly, PE firms necessitate that management makes a significant investment in the portfolio company, thereby exposing management further to downside risk (S. Kaplan & Strömberg, 2009). Management compensation often relies on illiquid equity stakes, which reduces the management's incentive to manipulate short-term performance (S. Kaplan & Strömberg, 2009).

In some contemporary literature, financial engineering, when considered beyond simple equity and debt, is defined as employing financial instruments or structures to manage a company's capital structure and risk profile. This definition can include instruments or structures such as derivatives, structured debt, securitization, and off-balance-sheet financing (Koller et al., 2020). Financial engineering can directly add value through means such as tax savings or a lowering in WACC[1], or indirectly by increasing the debt capacity, thereby enabling the company to raise funds for capturing more value-creating investments (Koller et al., 2020). The three most commonly applied tools of financial engineering are I) derivative instruments that transfer risks to third parties, II) off-balance-sheet financing that separates funding from the corporation's credit risk, and III) hybrid financing that introduces new risk/return financing combinations (Koller et al., 2020).

Scholars within corporate finance argue that an optimal capital structure is when companies minimize WACC, thus maximizing the company's value (Berk & DeMarzo, 2020). The optimal capital structure of PE-backed companies may differ due to factors such as dry powder in the fund and various incentive structures. Moreover, since debt is cheaper than equity, it enables the PE sponsor to generate a higher return on equity in portfolio

[1] Weighted Average Cost of Capital

companies. Throughout the ownership period, the PE fund must decide whether to distribute cash flows to investors or repay debt with these cash flows, thus normalizing the debt-to-equity ratio towards the divestment phase (Bennedsen et al., 2008). The typical capital structure of PE-backed LBOs consists of 70% or more debt in various forms, with the remaining 30% in equity (Rizzi, 2017). These capital structures are typically designed to be short-term, given the limited time horizon of the PE fund. The fund structure of portfolio companies leading to the limited liability of GPs, combined with the potentially high returns from excess returns[2], incentives substantial leveraged positions in portfolio companies. These financing practices can lead to higher prices for portfolio companies and further address the borrow cheap-buy-high phenomenon. In this scenario, PE funds aim to balance debt market conditions and equity investment attractiveness by identifying the maximum price they can pay for the company while still achieving the target Internal Rate of Return (IRR) for the investment (Rizzi, 2017). IRR is the discount rate at which the net present value of cash flows equals zero (Stowell, 2018).

The pricing process in an acquisition of a portfolio company based on Rizzi (2017):

- Initially, PE funds estimate the target purchase price based on recent comparable transactions, typically expressed as an EV/EBITDA multiple
- Next is an estimation of the required equity component based on the conditions of the portfolio company. Currently, the equity component is typically in a 30-40% range. The maximum amount of debt is determined based on the portfolio company's EBITDA. Banks are subject to regulatory criticism when NIBD exceeds 6x EBITDA. The bidder should only place a bid if the sum of the equity- and debt components exceeds the target price
- The final step is to calculate the expected exit price. Expected EBITDA growth is applied to the projected exit multiple, where debt is subtracted to derive equity value. The IRR can be calculated with the initial investment and the exit equity value. Hence, the PE fund would sign the deal if the projected IRR exceeds the hurdle rate.

Assessing the value generated from the tax shield of debt is complex. Findings show that variations from reduced taxes due to deductions of interest expenses span from explaining 4-40% of the firm's value, depending on assumptions and measurements (S. Kaplan & Strömberg, 2009). Additionally, it could be argued that it is challenging to measure the exact value derived from the tax shield. The above estimate is subject to critique, as the overall interest and tax rates have trended downward over the past decade, except from 2022 onwards.

3.3 Governance Engineering

Governance engineering is an approach that integrates active and efficient corporate governance practices into portfolio companies. Governance Engineering in PE refers to the deliberate and strategic modifications made to the governance structure of a portfolio company to increase operational efficiency, strategic clarity, and overall enterprise value. This often entails the creation of efficient reporting systems, establishing robust internal controls, and fostering a culture of transparency and accountability.

[2]Returns over the minimum hurdle rate

Definition 2: Governance Engineering

In this thesis, governance engineering is defined as the adaptive strategy by private equity firms to optimize flexible governance mechanisms, including dynamic management appointments and incentive structures, aiming to enhance portfolio company performance and value.

The objective is to improve management performance, encourage innovation, and align interests between stakeholders and management. Some of the primary components in governance engineering in PE are the following:

1. Board composition and effectiveness: PE firms often restructure the board to include experienced industry leaders and subject matter experts who provide strategic direction and oversight. Hence boards of PE-owned companies are smaller and have a higher frequency of meetings (Acharya et al., 2011; Bennedsen et al., 2008; Cornelli & Karakaş, 2008; Gertner & Kaplan, 1998).

2. Management incentives: Aligning the interests of management with those of the PE firm and other stakeholders is critical. This alignment is typically achieved through equity-based compensation plans, fostering a shared vision of value creation (S. Kaplan, 1989).

3. Monitoring and control systems: Effective governance requires robust systems for monitoring and control. PE firms install advanced systems to track performance, financial metrics, and operational efficiencies (Acharya et al., 2011).

Despite its benefits, governance engineering is not without challenges. These include potential resistance to change from existing management, risk of over-control leading to stifled innovation, and the inherent complexity of managing governance transitions (Stowell, 2018). Therefore, successful governance engineering necessitates a nuanced understanding of the firm's context, leadership dynamics, and industry specifics. Governance Engineering represents a crucial value-creation tool in PE, underlining the transition from passive investment to active ownership. With an ability to effect transformational change, it serves as a strategic approach to unlock value, thereby contributing to the success of the portfolio companies. However, its successful implementation requires a thoughtful strategy, professional expertise, and continuous adaptation to changing business environments.

3.3.1 Management Replacement

Management changes frequently in PE-backed companies: one-third of CEOs are replaced within the first hundred days of PE ownership, and the remaining two-thirds within the following four years (Acharya et al., 2011; S. Kaplan & Strömberg, 2009). This turnover can be attributed to the higher accountability in an LBO structure. Research indicates that such replacements often enhance company performance, with new CEOs engaging in M&A transactions that outperform their predecessors and streamlining operations by discontinuing non-core activities and reducing R&D costs and CAPEX (Alexandridis et al., 2019). New management often identifies and corrects operational inefficiencies and provides effective leadership to develop a new strategic direction, thus improving competitive moat, market share, and financial performance (Eisenhardt & Sull, 2001; Salomo & Leker, 2000). In essence, management change can act as a catalyst for value creation in a company, introducing new ideas, efficiencies, and strategic directions.

3.3.2 Active Ownership

Active ownership and close shareholder involvement can help to mitigate potential misalignment between the management's goals and shareholders' expectations in a company (Jensen, 1989). Typically, PE sponsors

acquire majority stakes in portfolio companies, allowing them to exercise full ownership and control. This control facilitates greater flexibility in decision-making and strategic implementation (Bennedsen et al., 2008). Shareholders differ regarding access to capital, competencies, and overall engagement. Consequently, a shift in ownership structure can enhance profitability and create shareholder value. PE ownership operates under a sense of urgency due to the typical 3-7 year holding period for portfolio companies. This time frame necessitates the board and management to formulate clear targets that maximize the company's value (Bennedsen et al., 2008).

3.3.3 Incentive-Based Remuneration

PE firms often encourage the target management team to invest their personal funds into the company. Such a financial commitment not only demonstrates their confidence in the business's potential but also instills a sense of ownership and responsibility. By providing the management team with a share of future profits or performance-based rewards, they are incentivized to strive for long-term success and value creation (S. Kaplan & Strömberg, 2009). Utilizing this incentive-based compensation model enables PE firms to optimize the potential and value of their investments, resulting in improved returns for the investors and a robust, more competitive portfolio of companies.

3.4 Operational Engineering

PE firms have evolved dramatically from their traditional role of providing capital to businesses. Over the last few decades, a paradigm shift has occurred in the PE landscape, with operational engineering becoming a cornerstone in value creation plans (Acharya et al., 2011; Achleitner et al., 2014; Bonini, 2015). This section delves into the concept of operational engineering and its growing significance in the PE industry. Operational engineering refers to the practices aimed at improving a portfolio company's operations to increase profitability and create value. These activities can span numerous areas, such as process optimization, supply chain management, human resources, technological advancements, and strategic restructuring.

Definition 3: Operational Engineering

In this thesis, operational engineering is defined as all strategic initiatives taken by PE funds to boost operational efficiency and profitability of their portfolio companies. It focuses on driving top-line growth, expanding profit margins, and implementing strategic changes, aiming to increase exit valuations.

Operational engineering is inherently complex, embodying many facets and nuances. When evaluating businesses, the academic consensus is that operations distinguish a specific firm; in contrast, the financing aspect of a business is considered replicable (Plenborg & Kinserdal, 2021). Beneath the concept of operational engineering lies a dynamic space of possibilities and trade-offs. To comprehend causality in operational engineering, one might envision various value-creation plans for a given business, each yielding a different output. Operational engineering can be further divided into two categories: top-line growth and operational improvements. The following subsections will delve deeper into these distinct value-creation mechanisms.

3.4.1 Top-line Growth

Growth potential is often highlighted as an attractive characteristic of a strong buyout candidate, and PE funds leverage their competencies to implement growth strategies. Some of these common growth strategies are based on the following concepts:

Buy & Build
GPs can utilize established portfolio companies as platforms to accelerate growth. They often execute add-on acquisitions to these companies to stimulate growth. GPs can target small companies outside the scope of larger corporations, thus potentially reducing costs. During economic downturns, owner-operated companies may be increasingly motivated to sell at lower prices, enabling add-on acquisitions to reduce the overall entry multiple of the investment case (Stowell, 2018). These add-on acquisitions also enhance the potential for a trade sale, as the size of the portfolio company is a significant factor for strategic buyers (Stowell, 2018).

Organic Growth
Organic growth is typically achieved through developing new products or entering new markets, which usually require investment in R&D, CAPEX, and NWC[3]. The portfolio company can aim to expand its market geographically or address new customer segments. Portfolio companies entering new markets experienced higher growth in sales compared to firms that do not (Birshan & Kar, 2012).

Pricing optimization
Seeks to adjust the pricing of products and services to a pricing equilibrium to improve profitability and enhance sales growth. Research in pricing optimization stipulates that pricing optimization can effectively increase sales, especially in industries with low margins and high price sensitivity (Hinterhuber & Liozu, 2014).

Growth Strategies and Shareholder Value
Figure 3.2 displays an analysis of different growth strategies and shareholder value created for incremental one dollar of revenue in companies focused on consumer products. The analysis is assumed to reflect a broader reality, as the authors obtained examples of margins and capital requirements for several industries and customer segments (Koller et al., 2020). Additionally, the intervals of return on capital will vary across sectors and industries. The primary objective of the chart is to identify the differences and ranges in return on capital of different growth initiatives.

[3]Net working capital

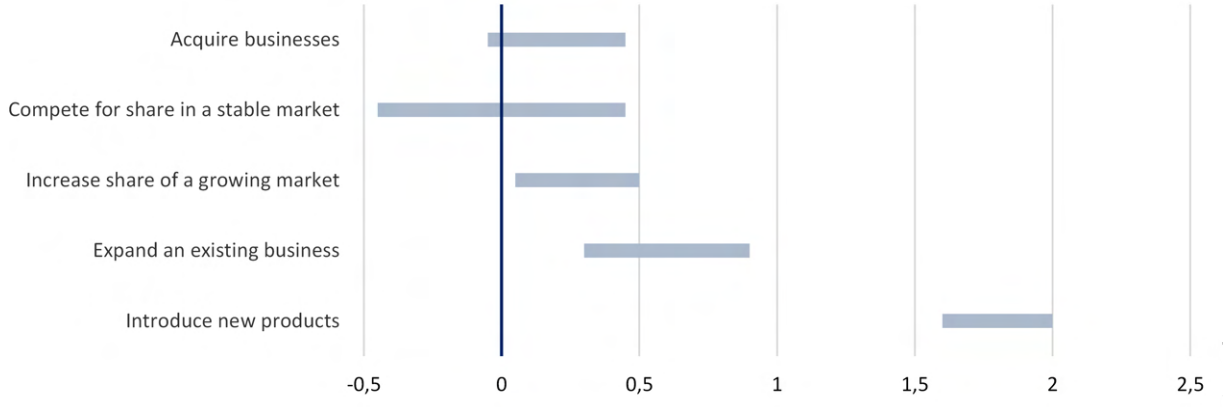


Figure 3.2: Growth Strategies and Shareholder Value

Source: (Koller et al., 2020), Authors creation

Each additional dollar of revenue from an add-on acquisition creates a value ranging from -0.5 to 0.45 dollars for shareholders. Consequently, add-on acquisitions are considered one of the least favorable growth strategies in terms of value creation for shareholders. Introducing new products generates the highest return for shareholders, with a value ranging from 1.6 to 2 dollars for every dollar of revenue. Additionally, expanding an existing business and gaining market share in a growing market are identified as attractive initiatives regarding shareholder value. On the other hand, competing for a share in a stable market at the lower end of the range seems unattractive, as it involves increased risk due to investment in assets to support growth.

3.4.2 Operational Improvements

This subsection explores the value creation plans (VCPs) implemented by PE firms. These plans consist of initiatives and strategies uncovered by Biesinger et al. (2020). VCPs are concrete plans targeted at enhancing operational performance. By exploring these strategies, a deeper understanding can be gained regarding the focus areas and potential trade-offs between the fundamental drivers of operational value creation.

Buy/Upgrade Assets

The most commonly observed VCP post-buyout is buying or upgrading assets, as illustrated in figure 3.3. The idea of buying and upgrading assets comprises plans that involve the purchase or improvement of fixed assets, thereby increasing CAPEX (Biesinger et al., 2020). This approach hinges on the fundamental principle of acquiring undervalued or underperforming assets, enhancing them, and ultimately selling them at a higher value. Firstly, firms meticulously identify and acquire assets that promise substantial growth potential. These can include businesses facing financial difficulties, underutilized resources, or those lacking strategic direction. Given extensive industry expertise and resources, PE firms can determine the intrinsic value of these assets and the potential benefits that others might overlook. Following the acquisition, the strategy shifts to the improvement phase. The enhancement initiatives often include operational efficiency measures, strategic redirection, financial restructuring, or infusion of technological advancements, depending on the nature and context of the specific asset (Stowell, 2018).

Selling Existing Assets/ Divest, Spin-Off divisions

The phrase *returning to core business* frequently echoes throughout the corporate world. However, actions such as selling off existing assets and implementing divestitures or corporate spin-offs are typically not the main strategic focus for PE owners before a buyout. Yet, post-buyout, these strategic measures often gain importance, becoming central to the restructuring plan (Biesinger et al., 2020). Asset divestiture involves selling non-core or underperforming assets, strengthening the company's financial position by generating immediate cash, reducing debts, and concentrating resources on the core business. This strategy also optimizes the rate of asset utilization, thereby improving overall operational efficiency. Spin-offs, conversely, involve separating a division or a subsidiary from the parent company to create an independent entity. This strategy allows for enhanced focus on the separated division's growth potential, strategic alignment, and operational independence. Furthermore, it tends to increase shareholder value by creating pure-play entities that are often better understood and more highly valued by the market (Koller et al., 2020).

Reducing Costs

Cost reduction within a firm can come in endless forms; cutting costs can be levered into effect through various initiatives like trimming the workforce, implementing suitable technologies, streamlining logistic operations, and the list goes on. Reducing costs is clearly at the center of attention for GPs before and after the buyout. In the revised action plan, reducing costs is even more in focus (Biesinger et al., 2020). Creating a market for a product or service relies heavily on the interest and demand of consumers. If there is no demand for the product or service, creating a market becomes challenging, if not an impossible task. This is because the demand side of the equation is largely outside the company's direct control, influenced by external factors like consumer preferences, economic conditions, and competitive offerings. However, cost reduction is a different story. Unlike creating market demand, cost reduction falls directly within a company's circle of influence. This is because a company controls its operational processes, supply chain management, financial structure, and other aspects contributing to the cost of delivering a product or service. Thus making cost reduction an achievable and concrete goal requiring strategic vision and capabilities in which PE funds specialize.

Margin Expansion

Private equity firms often employ cost reduction strategies during the first years of the holding period to capture low-hanging fruits in terms of cost savings within portfolio companies. This approach seeks to maximize short-term value by targeting readily achievable cost-saving opportunities (S. Kaplan, 1989). Methods used include renegotiating contracts with suppliers and customers and optimizing pricing for improved margins. Portfolio companies' overhead costs are commonly benchmarked against industry peers, providing opportunities for cost reduction through function consolidation, staff reduction, or contract renegotiation (Stowell, 2018). Considering the typical cycle, with portfolio companies ideally divested after a 3-7 year holding period, practitioners may prefer short-term performance gains. This can involve allocating resources towards initiatives that yield quicker returns, potentially shifting focus away from long-term value creation (Spliid, 2007). Emphasizing the effectiveness of pricing optimization as a value creation tool, McKinsey demonstrated a 3-7% margin expansion within a year for PE-backed companies. They suggest that factoring potential pricing improvements into decision-making can bolster PE firms' confidence in potential upside and provide a competitive advantage. For a typical midsize US company, a 1% improvement in pricing can boost profits by 6%, while 1% reductions in variable and fixed costs increase profits by 3,8% and 1,1%, respectively (Baker et al., 2019).

Managing Capital Requirements

GPs may discontinue underperforming R&D initiatives and minimize non-essential CAPEX to promote growth.

This strategy is intended to optimize resource allocation towards activities with the most potential for value creation in the portfolio company (Biesinger et al., 2020). By eliminating inadequate R&D and curtailing non-essential CAPEX, GPs can enhance profitability and cash flow, freeing resources for investment in more promising growth opportunities. Improving working capital management can be a tool to ensure adequate short-term liquidity for the portfolio company. GPs can optimize inventory turnover to reduce surplus stock and improve the company's working capital. Efficient processes can be implemented for accounts receivable and payable. Furthermore, non-core assets from discontinued operations can be divested, providing resources for debt service or growth strategy financing.

3.5 Value Creation Plans

Biesinger et al. (2020) published an extensive study on value creation plans in PE. The authors utilized LASSO[4] regression to regress combinations of VCPs against returns. Figure 3.3, provided below, offers an overview of the 23 VCPs. It illustrates the percentages of deals pursuing individual items in the initial and revised value creation plans. The revised plan is defined as either a modification or the introduction of a new action plan after the first year of the holding period.

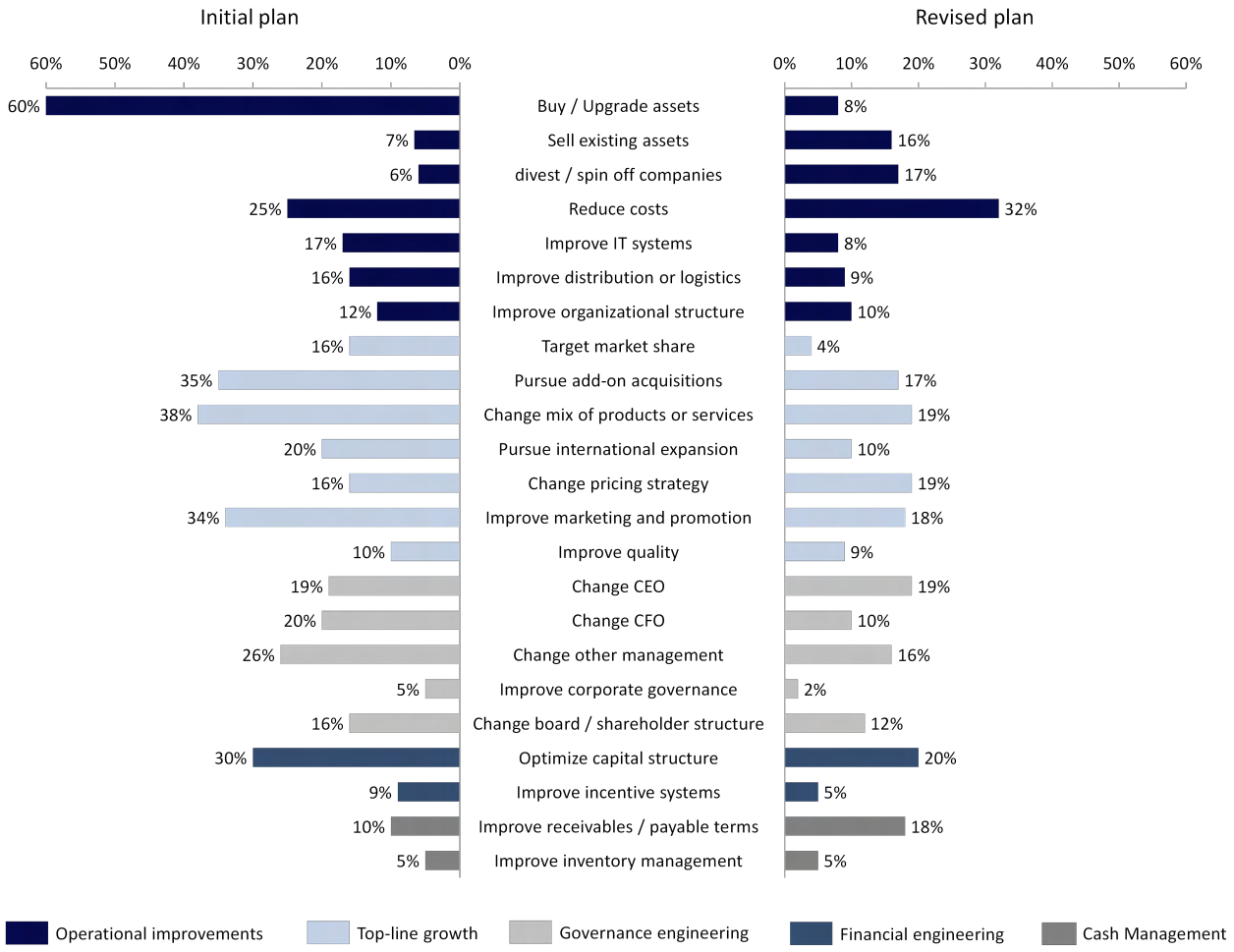


Figure 3.3: VCPs: Initial Plan Vs. Revised Plan

[4]Least absolute shrinkage and selections operator

Source: (Biesinger et al., 2020), Authors creation

The sample consists of 1580 deals, with 77.3% experiencing a revision in VCPs. The figure illustrates areas GPs empirically are focusing on during the holding period. Some strategies complement each other, while others are vastly different. Certain strategies are feasible for specific types of companies, but trying to excel in all areas could lead to disaster.

Each VCP has multiple layers and requires thorough, actionable plans for successful implementation. Biesinger et al. (2020) demonstrate systematic variation in VCPs over time, suggesting they are tailored to the unique circumstances of each portfolio company. Significantly, all five main value-creation strategies have grown in popularity, indicating that PE firms are taking a more active role in their portfolio companies. An important finding from the study is that the success rate of a VCP item is more likely to be higher if similar initiatives are pursued by the fund's other portfolio companies, particularly concerning governance engineering and operational improvements. Furthermore, post-implementation strategy combinations proved better predictors of realized returns than pre-implementation combinations, suggesting that the successful execution of VCPs is a key driver of returns.

The study predicts that combining top-line growth, governance engineering, and financial engineering strategies will yield the highest returns. A considerable 84% of sampled deals implemented operational improvements, 74% pursued top-line growth strategies, 48% enacted governance engineering, while 35% and 14% respectively undertook financial engineering and cash management initiatives. Interestingly, the initial plan to buy or upgrade assets was significantly reduced after the first year of the holding period, dropping from 60% to 8% of deals. Incorporating a cost-cutting plan in the revised plan gained popularity, emphasizing that PE firms are committed to taking all necessary measures and doing whatever it takes to create value. Interestingly, the prospects for CEO replacement remain constant after the first year, accounting for 19% of deals. Plans to pursue add-on acquisitions were heavily revised after the first year, possibly indicating that a proportion of add-on acquisitions are completed in the transaction year. In contrast, plans to continue pursuing add-on acquisitions remain high (20%), signifying that buy-and-build strategies are popular in the PE industry. Alternatively, it could suggest that PE funds lower their ambitions regarding inorganic growth strategies during the first year.

The paper by Biesinger et al. (2020) provides valuable insights into potential VCPs for PE funds. It demonstrates that VCPs are not static; they evolve in response to each portfolio company's unique circumstances. This analysis suggests that PE funds engaging in secondary transactions may uncover appealing, untapped value-creation opportunities left by the first acquirer. The question remains whether secondary sponsors are more successful in implementing these VCPs.

3.6 Decomposing Sources of Value Creation

Analyzing the sources of value creation, there is a widespread preference among academic scholars and practitioners for using EBITDA as the primary metric to calculate enterprise value. EBITDA is a reliable proxy for cash flow, which is crucial for the DCF and LBO model that relies on long-term cash flow projections based on EBITDA (Stowell, 2018).

A paper from Capital Dynamics investigates sources of value creation in PE. The study identifies operational improvements, leverage, and increasing multiples as the key drivers of value creation. To examine the effect, the paper analyzes the enterprise values of 241 exit transactions globally. The comparison is made by assessing the EV/EBITDA ratios at both entry and exit while considering market multiples relative to a publicly listed benchmark. The paper's findings reveal that operational improvements contribute to 51% of the value creation, as depicted in figure 3.4, making them the primary source for achieving higher enterprise value upon exit (Capital Dynamics, 2014).

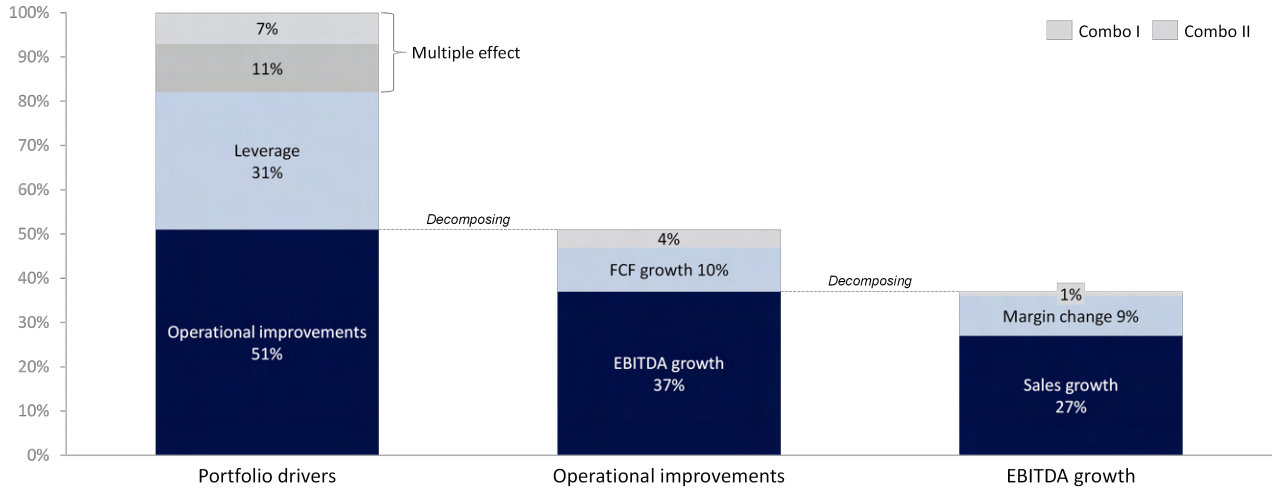


Figure 3.4: Decomposing Drivers of Value Creation

Source: (Capital Dynamics, 2014), Authors creation

The graph illustrates the sources of value creation and provides a step-wise decomposition of the operations component. The first bar demonstrates that 31% of the growth in enterprise value is attributed to leverage, which is associated with financial engineering. However, the primary driver is operations, which is connected to operational engineering. The effects of multiples can be further analyzed into market multiples (7%), driven by market deal values, and GP multiples (11%), representing the ability of GPs to enhance asset quality through gaining market share, creating brand value, diversifying the customer base, and other factors (Capital Dynamics, 2014). Digging deeper into operations, it is revealed that 37% of operational improvements can be attributed to growth in EBITDA. At the same time, the contribution of cash flow amounts to 10%, and a combination of the two factors accounts for 4%. Further decomposing EBITDA growth, it becomes evident that sales growth dominates as the primary driver, accounting for 27% of EBITDA growth. This correlates with PE firms' focus on top-line growth in VCPs. Additionally, margin change contributes 9% to the growth in EBITDA. This representation of enterprise value growth and value creation strengthens the argument that operations are vital in driving value creation within PE, resulting in higher valuations towards the divestment phase. Moreover, it underscores the significance of sales and EBITDA growth when evaluating the operational performance of portfolio companies.

3.7 The Private Equity Toolbox in Summary

Based on the examination, it is clear that the private equity toolbox is a complex framework comprising various components and sub-components. Each facet of the toolbox carries its distinct details and nuances. Navigating this complexity is not just a necessity but a craft in itself. The intricacies and trade-offs that lie with the choices made with the strategic focus of specific VCPs are analogous to:

Private equity firms are like photographers with a single roll of film. They can't take every shot; they must carefully choose which scenes hold the most value and are worth capturing.

Furthermore, several VCPs exhibit complementarity, with financial and governance engineering sharing more similarities than operational engineering. However, successful ownership entails a strategic approach that incorporates elements from all aspects of the toolbox, leveraging the complementary effects of different tools. Financial engineering directly influences valuation through tax savings and lower funding costs, as well as indirectly by securing investment opportunities for growth. In the operational engineering aspect of the toolbox, it is clear that transaction values are closely tied to projected EBITDA, which, in turn, relies on sales growth and margin expansions. Capital Dynamics (2014) highlights that operational improvements are the primary driver of value creation. EBITDA growth, predominantly influenced by changes in margins and sales, plays a key role. PE firms have ample opportunities to employ governance engineering, create engaging boards and implement incentive-based compensation to align interests. Furthermore, the governance of portfolio companies under PE ownership emphasizes flexibility and adaptability.

Biesinger et al. (2020) specifically identified 23 VCPs implemented by PE firms. These plans are derived from the three engineering boxes. Furthermore, the toolbox chapter identified determinants of operational value creation, which can be used to establish the hypotheses addressing the research questions of the thesis.

4.0 Literature Review

In previous chapters, the fundamental operating principles of PE funds have been outlined. These principles involve GPs raising capital from LPs. Returns are generated by acquiring target companies using leverage, creating value in the portfolio companies, servicing debt with free cash flow, and ultimately divesting portfolio companies, wherein GPs earn carried interest in addition to the management fees collected during the fund's lifecycle. As the operating principles of PE funds intersect with multiple disciplines within the academic literature, this chapter reviews related studies, focusing on the themes of LBOs, the operating performance of SBOs, and the conventional drivers of operational value creation. The objective of the research questions makes it vital to identify drivers in the existing literature to establish a reliable and robust foundation for analytical measures, thus ensuring validity and comparability across previous studies.

Approach of the Literature Review
The literature review is based on a systematic approach (Boland et al., 2017). The systematic literature review is an academic method aimed at minimizing bias and ensuring reliability and nuance to the reader, avoiding hand-picking specific literature supporting the analysis of the thesis. By incorporating various research methodologies and results, this methodological tool facilitates a comprehensive assessment of the existing literature (Boland et al., 2017). Upon reviewing and synthesizing the data, insights are drawn regarding the research question. Such insights shed light on the strengths and limitations of the existing body of literature and provide suggestions for future research avenues. This approach facilitates the identification of potential discrepancies across various methodological approaches and findings within the prevailing literature, thereby ensuring a more holistic understanding of the research field.

4.1 Leveraged Buyouts

By 1970, conglomerate divestitures surged, making up 53% of company transactions in 1977. Kohlberg recognized this and believed many firms could become profitable private entities. Kohlberg Kravis Roberts & Co. (KKR) was established in 1976, pioneering and popularizing PE (Kaufman & Englander, 1993). As LBOs were a value-generating phenomenon, academic research began exploring underlying value drivers, structures, and characteristics. Steven Kaplan and Michael Jensen provided the earliest studies on PE. The central question in academic research on PE is directed toward value creation. However, since the 1970s, there have been significant changes in the PE industry. Naturally, competition has increased, the industry has matured, and good deals are harder to come by. Consequently, the sophistication of funds has magnified significantly. At the origin of PE in the 1970s, there were two exit routes; an IPO or a trade sale. Through the evolution of PE, SBOs have caught up from being 2% of all exits in the years 1970-1984 to comprising 31% of all exits in 2003-2005 (S. Kaplan & Strömberg, 2009). This section will provide insight and an overview of the most influential research on value creation in PE. The aim is to identify factors that are essential in assessing value creation in PE.

4.2 Traveling the Path of Private Equity Research

The following subsection reviews key literature on LBOs, ranging from early research to more contemporary studies, to offer a comprehensive understanding of original perspectives on PE and LBOs. This wide lens subsequently narrows to a specific focus on SBOs, identifying research gaps and areas compelling for analysis. To fully grasp the complexities of SBOs, it is crucial to explore the rich body of LBO literature since these two share similar deal structures, financial mechanisms, and risk profiles. The wealth of knowledge derived from extensive LBO literature is the foundation for understanding SBOs. In curating the literature for this review, emphasis is placed on the relevance and impact of the research, its citation frequency, and the robustness of the peer-review process it has undergone. This selection process ensures the inclusion of only authoritative and credible studies. In addition, to maintain a comprehensive understanding of LBOs, the review considers a diverse collection of articles, each contributing to a balanced and multifaceted viewpoint

Jensen (1989)
Jensen argues that the public corporation was dominant during the 1960s and 70s, yet the escalation of LBO activity in the 1990s facilitated the emergence of new organizational structures that bolstered governance and enabled value creation. The primary argument revolves around the misalignment between management and shareholder incentives, an issue ostensibly remedied by private ownership and incentive-based remuneration. Jensen also underscores the LBO premium, which averaged 50% at the time, reinforcing the notion that management in public corporations could potentially erode massive amounts of value without facing a significant threat of disruption. Further, he contends that debt compels value creation, its inherent nature serving as a potent catalyst for change. Thus, management incentives in LBOs are predicated on a robust correlation between pay and performance (Jensen, 1989). Jensen distinctly advocates for a private ownership structure for organizations facing limited growth opportunities. Moreover, he maintains that a low level of debt and excess cash can spur management to engage in empire-building activities, often damaging shareholder value.

Kaplan (1989)
In a paper from 1989, Kaplan investigates management buyouts (MBOs) in the context of operating performance and value creation. The sample is based on buyout companies delisted from the NYSE from 1980 to 1986. The sample contains a total of 76 buyouts. Operational performance is measured by accessing financial statements in the following time windows around the buyout transaction; [-1 : +1], [-1 : +2], and [-1 : +3]. Measurement is based on median values, and the paper utilizes a Wilcoxon signed rank test in assessing operating performance relative to control groups. Kaplan finds that companies subject to an MBO experience increases in EBIT and cash flow while CAPEX is reduced. Buyout companies exceed industry changes in the period by approximately 50%, measured by net cash flow to assets and sales, which is primarily driven by increases in EBIT and decreases in CAPEX. Pre-buyout investors earn a combined median total market-adjusted return of 77%. The median post-buyout growth in employees is 0,9%, indicating that investors do not benefit from large headcount reductions.

Kaplan & Stein (1993)
The paper by Kaplan and Stein evaluates alterations in pricing, capital structure, and investor returns. It scrutinizes 124 MBOs executed between 1980 and 1989, employing nonparametric rank tests to compare the values of different variables across three periods. Kaplan and Stein discern an escalation in buyout price-to-cash-flow ratios, especially for transactions financed with junk bonds. This trend indicates that buyouts have become riskier and involve higher leverage ratios. Additionally, the paper emphasizes a shift in capital structure,

with banks assuming smaller roles in deals, supplanted by public junk bond financing. This shift has resulted in more precarious capital structures and an increased probability of financial distress, suggesting an overheating of the buyout market. Although further research is required to fully comprehend the decisions of junk bond investors, the paper constitutes a valuable resource, offering critical insights into the dynamics of the buyout market in the 1980s (S. N. Kaplan & Stein, 1993).

Vinten (2007)

Contrary to other academic scholars, Vinten investigates the performance of 73 Danish buyout companies from 1991 to 2007. The paper employs Ordinary Least Squares (OLS) regression to assess the average post-buyout impact of PE fund ownership. For evaluating operating performance, the time series is divided into three distinct periods: 1-2 years, 3-5 years, and over five years post-buyout. The sample, consisting of PE-backed and non-PE-backed companies, is compared to a benchmark set of 545 companies to measure abnormal operating performance. Control groups are defined based on NACE classifications and further delineated by a balance sheet size criterion determined by total assets. The main finding of the paper is that PE fund ownership negatively impacts firm performance in comparison to non-PE-backed companies. Vinten underscores that the touted superior corporate structure of LBO companies does not align with data since post-buyout ownership concentration decreases, and debt does not lead to efficiency improvements. In addition, Vinten notes that portfolio companies pay out higher dividends than benchmarks, but the data sample provides no evidence of a reduction in the workforce (Vinten, 2007).

Guo et al. (2009)

Taking distance from the 1980s, a paper from 2009 provides a comprehensive study of LBOs from 1990 to 2006. Using a sample of 192 buyouts, the authors conclude that LBOs yielded substantially smaller gains in operating performance than LBOs investigated in the 1980s. The performance of these LBOs is evaluated against benchmarks determined by standard industrial classification (SIC) codes, with differences examined using OLS regression. Mean sample values are analyzed using a two-tailed t-test, while the Wilcoxon signed-rank test is employed for median sample values. Various measures of profitability and return assess operational performance. The sample is examined through the following time series: [-2 : -1], [-1 : +1], [-1 : +2], [-1 : +3], and [-1 : exit]. Additionally, the paper uses cross-sectional regressions to shed light on the relative importance of various factors contributing to returns, including management incentives, management replacement, benefits of increased debt, and improved governance and monitoring. The study highlights the commonality of multiple financial sponsors and significant asset restructuring. The analysis unveils considerable positive returns in LBOs, with operating performance gains paralleling or slightly exceeding benchmark firms. However, the authors caution that these returns may not be sustainable without ongoing operational gains under less favorable market conditions. The paper also identifies changes in operating performance, industry valuation multiples, and the tax benefits of debt as key factors contributing to returns. A crucial discovery is the positive correlation between CEO replacement at or soon after the buyout and improved operating cash flow. The paper concludes that understanding these LBO structures and their value creation methods is crucial for the prospects of these highly levered firms. The authors caution that any significant declines in cash flows and valuation multiples could impede the ability of PE firms to exit transactions with positive returns (Guo et al., 2009).

Kaplan & Strömberg (2009)

Kaplan and Strömberg offer an exhaustive examination of PE firms and their investment strategies, paying particular attention to LBOs. The authors point out that PE firms have diversified considerably, adopting various investment strategies beyond LBOs. These include venture capital, growth equity, distressed debt,

and real estate investing. The paper underscores the significance of operational improvements within portfolio companies as a primary driver of PE returns. It is noted that these firms frequently enact cost-reduction measures and other efficiency enhancements to stimulate profitability. The authors also delve into the function of debt financing in LBOs. They explain that although high debt levels can amplify risk, such debt can also deliver tax advantages and harmonize incentives between investors and management. The paper presents a detailed synopsis of the evolution and history of PE, tracing its roots back to the 1960s and 1970s when it specialized in LBOs. Finally, the authors touch on the potential disadvantages of PE investing, encompassing high fees and limited liquidity. They remark that these factors might render PE less appealing to certain investors (S. Kaplan & Strömberg, 2009).

4.2.1 Summary of LBO Literature

In summary, there seems to be evidence of superior and inferior operating performance in LBOs and MBOs across the literature. There seems to be some homogeneity around methodological approach and measurement, as several studies measure the effect of buyouts in the following time windows; [-1 : +1], [-1 : +2], and [-1 : +3]. Further, the selection of statistical tests seems to be somehow congruent with focusing on various regression forms and statistical tests. The figure below displays a summary of the key findings of the reviewed literature concerning LBOs and MBOs:

Table 4.1: Key Findings on LBOs

Author & Year	**Sample**	**Key Findings**
Jensen, 1989	US	The LBO structure is superior in reducing agency costs thus maximizing shareholder value
Kaplan, 1989	US	MBOs lead to increased EBIT (24% higher in the third year post buyout), decreased CAPEX (20%), and improved net cash flow
Kaplan & Stein, 1993	Global	MBOs create value, but especially deals financed with junk bonds impose substantial default risk. MBOs experience gains in operating performance, driven by revenue growth, cost cutting, and improved efficiency
Vinten, 2007	Denmark	PE fund ownership significantly negatively affects firm performance compared to non-PE-backed firms. Post-buyout ownership concentration falls, and debt does not lead to efficiency improvements
Kaplan & Strömberg, 2009	EU	Operational improvements are the key driver of returns. High levels of debt can increase risk but can provide tax benefits and align incentives between investors and management
Guo et al., 2011	US	Cash flow gains are greater for LBO targets with greater increase in leverage. Gains in operating performance in LBO companies are slightly higher than benchmarks. CEO replacement entails greater cash flow performance

4.3 Key Literature on SBOs: A Comprehensive Overview

The academic landscape surrounding SBOs has surged in recent years. This section begins with elucidating the scope, geographic focus, findings, and methodologies employed in these research studies. Subsequently, commonalities and divergences in various motivations for engaging in SBOs are synthesized, shedding light on

areas of consensus and points of contention. This comprehensive exploration ultimately facilitates identifying existing research gaps and areas that demand further exploration.

Bonini (2015)

Bonini examines the complexities of operational value creation and the factors influencing investment decisions in European SBOs. The selection is motivated by the stringent disclosure requirements prevalent in the region. Covering a period from 1998 to 2008, the dataset is refined from an initial pool of 2911 deals to a sample size of 326. The study examines a time series of [-1 : +2] resulting in four years of financial data. The paper utilizes OLS regression to capture changes in operating performance supplied by univariate and logistic regression. Bonini performs a parametric t-test based on normalized and centered values. Moreover, to mitigate the influence of outliers, a nonparametric Wilcoxon signed-rank test is employed to assess the median performance estimates to the null hypothesis of no change in the selected metrics. This test serves as a robust control mechanism against extreme observations. The performance benchmarking method involves comparing two consecutive buyouts of the same company, from the first to the second buyout. Bonini evaluates operating performance using a variety of accounting ratios, such as EBIT and EBITDA margin for operating ratios. Bonini identifies abnormal performance as the excess return of the ratio compared to the industry peer group median and as excess growth compared to the same group. This growth excess benchmark accounts for industry variations. Control groups are selected by assessing SIC codes. Bonini discovers that PBOs significantly outperform SBOs in nearly all metrics, with SBOs only displaying a higher Net Debt/EBITDA ratio than PBOs. Bonini's findings reveal that PE-backed companies experience an increase in abnormal operating margins after the first buyout. However, during the second round, margins decline and ultimately revert to the industry average. It is explained that SBO activity is determined by debt market sentiment. Furthermore, Bonini investigates the potential collusion narrative but finds no evidence to support the existence of reciprocity (Bonini, 2015).

Wang (2012)

Wang's research aims to uncover the motivations behind engaging in SBOs by examining three primary factors: efficiency gains, liquidity-based market timing, and collusion. Focusing exclusively on buyouts in the UK from 1997 to 2008, the study's final sample consists of 485 PBOs and 140 SBOs. Wang measures in the following time series; [-1 : +1], [-1 : +2], and [-1 : +3]. The methodological approach employed involves comparing the median values of the PBO and SBO samples. As a result, Wang does not conduct a direct comparison of subsequent buyouts but instead examines the aggregate-level characteristics of the samples. Wang measures abnormal performance by comparing metrics to industry peer medians based on SIC codes, thus eliminating market effects. Efficiency gains are evaluated based on various EBITDA and profit margin metrics. Wang utilizes probit regressions, Heckman's selection model, and OLS regression to assess change in operational metrics. Applying the Wilcoxon signed-rank test to the [-1 : +3] time window, Wang finds that SBOs demonstrate significantly improved performance in EBITDA/fixed assets. Although the analysis presents mixed evidence concerning the efficiency gains motive, the study concludes that SBOs do not enhance the target companies' efficiency. Wang further explores how liquidity conditions influence exit choices in the market. The results indicate that during periods of strong equity market performance, PE funds are more likely to opt for IPOs rather than SBOs as their exit route. Lastly, Wang investigates the possibility of collusion among market participants. The analysis, however, uncovers no evidence to suggest the presence of such behavior in the data (Wang, 2012).

Freelink & Volosovych (2012)

Complementing the research on SBOs in the UK, a study examines a sample of 101 SBOs from 1999 to 2008.

The analysis measures the entire ownership period, from one year before the buyout to the year before exit, to determine whether SBOs create value for financial sponsors. Primarily, the study focuses on return on sales and assets, using EBITDA and EBIT in the numerator to gauge operational value creation. The paper utilizes two linear regression models and a two-sample Wilcoxon-Mann-Whitney rank-sum test to assess cross-sectional differences in measured operating performance. Moreover, the authors employ OLS regression to evaluate the influence of various hypotheses on the sample measures. The findings demonstrate that operating metrics in SBOs perform significantly worse after accounting for industry effects and without adjustments. However, despite the decline in operating performance, the analysis exhibits that the returns to financial sponsors from SBOs are considerably lower than those from PBOs. Interestingly, these returns still significantly outperform industry peers (Freelink & Volosovych, 2012).

Arcot et al. (2013)

The dataset analyzed is extensive, consisting of 4328 LBOs, including 1274 SBOs, across the US and 12 European countries from 1980 to 2010. The research seeks to examine adverse agency problems associated with PE contracts and to explore the potential existence of certain incentives within buy and sell pressures. These incentives could be diversionary effects resulting from the finite lifespan of a PE fund. The study measures the operating performance of portfolio companies within the time window $[0 : +6]$. The paper employs multivariate logit regression to test the hypothesis that PE fund characteristics can be proxies for investment incentives and predict secondary transactions. Additionally, a multivariate logistic model tests the hypothesis that PE fund characteristics can serve as proxies for investment incentives and predict secondary exits. A t-test is further utilized to test for differences in means and medians. The study concludes that PE funds are highly likely to engage in exit or acquisition activities when confronted with pressure to sell or buy, owing to the inherent investment and divestment periods stipulated by the fundamental lifecycle of PE funds. This pressure, present on both the buying and selling sides, contributes to an impact on valuation, ultimately affecting value creation for both the buying and selling funds (Arcot et al., 2013).

Plagborg-Møller & Holm (2017)

A research paper that explores the nuances of exit choices made by PE funds investigates the exit decision between IPOs and SBOs. This study analyzes a sample of 88 PE exits in Denmark and Sweden from 2003 to 2013. Probit regression is employed to examine the influence of various metrics on exit choice. Additionally, a Chow test is applied to determine whether the impact of portfolio company factors significantly differs before and after the financial crisis. The findings suggest that better-performing portfolio companies are more likely to choose IPOs as their exit route and vice-versa. Furthermore, the study identifies equity market performance, debt market spreads, and GDP growth as pivotal factors influencing exit choice. Ultimately, it is revealed that the performance and size of portfolio companies play a significant role in determining the PE exit route (Plagborg-Møller & Holm, 2017).

Degeorge, Martin, and Phalippou (2015)

A study addressing concerns about value creation scrutinizes the timing of SBOs in a fund's investment phase and investigates whether SBO buyers can bring additional value to portfolio companies. The research delves into the potential for value creation through the complementary skills of lead partners in funds and LP overlap to enhance the understanding of the subject. The study is based on a final sample of 231 SBOs and 3240 PBOs. The paper employs OLS regression with investment duration as the dependent variable, and a t-test is applied to test for differences in means and medians. The time series for measuring operational value creation extends from $[-1 : +3]$, encompassing five years of financial data. The study reveals that late SBOs generate a negative net

present value for LPs invested in the buying fund. On average, late SBOs return $0.88, whereas an investment in a stock market index would have returned $1. Essentially, SBOs act as a money-burning device that enables the PE fund to deploy dry powder, particularly as the fund approaches its maturity stage. It is noted that the complementary skills of subsequent financial sponsors, such as a regional PE fund followed by a global one, greatly contribute to value creation. Lead partners are categorized into two main skill sets: operational, representing partners with consulting or industry management experience, and financial, representing partners with a background in financial fields such as investment banking. The paper finds that SBO transactions between firms with complementary skill sets generate significantly higher returns for LPs than SBOs between firms with similar skills. Finally, the research concludes that LP overlap does not incur additional transaction costs for investors (Degeorge et al., 2015).

Achleitner & Figge (2014)

This paper evaluates whether SBOs exhibit comparable value creation properties and generate distinct returns compared to PBOs. A total of 2456 buyouts are examined, including 448 SBOs, spanning the period from 1990 to 2010. Transactions from North America and several European countries comprise the geographical scope of this study. The comparative analysis between SBOs and PBOs hinges on three value creation metrics: operating performance, leverage, and pricing. Moreover, the study assesses if SBOs yield lower equity returns. Using OLS regressions, Achleitner and Figge explore differences in operational performance between these two types of buyouts. Measurement within the time window of [-1 : +1] reveals that SBOs provide equivalent returns on equity and demonstrate parallel operational performance to PBOs. However, a significant divergence emerges in the leverage component, as SBOs exhibit a 28-30% higher leverage, gauged through debt/EBITDA. Concluding observations find that SBOs command a premium, being 6-9% costlier than other forms of buyouts (Achleitner et al., 2014).

Sousa & Jenkinson (2015)

This investigation delves into the timing and choices of PE exits, utilizing data from 1022 European portfolio companies between 2000 and 2014. During the complete holding period, financial metrics undergo measurement. A trinomial logistic regression model, with exit routes as dependent variables, is employed by the authors. Significance levels of average differences hinge on a two-tailed student t-test, while variations rely on a one-sample Wilcoxon sign-rank test. Due to extreme outliers and skewed distributions within the sample, the variables are either winsorized or measured in natural logarithms. Discoveries from the analysis show that market conditions heavily influence the exit choices of PE funds. As an illustration, during prosperous equity markets, an IPO becomes a more prudent and probable exit strategy. Conversely, SBOs turn more likely when a pessimistic outlook mars equity markets. Furthermore, the inclination towards the SBO exit route heightens when the portfolio company showcases robust cash flow and lower CAPEX needs, enabling the entity to maintain elevated debt levels. It also emerges from the study that funds further along in the investment period show a tendency to acquire a company from another PE fund (Jenkinson & Sousa, 2015).

Research Published by CBS Students

Two master theses from Copenhagen Business School examine the potential inferior operational performance in SBOs versus PBOs within Denmark, Sweden, and Norway from 1999 to 2014. Skibsted and Thelin (2018) conclude that SBOs markedly underperform PBOs concerning abnormal operating profitability metrics, such as EBITDA-margin and EBIT-margin. SBOs also demonstrate lower operating performance in terms of EBITDA and sales growth. Moreover, SBOs display a greater increase in debt multiples compared to PBOs. This analysis employs OLS regression, and the student's t-test and Wilcoxon signed-rank test are utilized to test if the true

population value is zero for mean or median. Further examination of value-creation drivers and their impact is conducted via OLS-based multiple linear regression models (Skibsted & Thelin, 2018). The findings stem from database-extracted financial data with a measurement time window from [-1 : +2].

Another study, conducted by Foldager and Mølbak in 2020, probes into operational value creation in SBOs and PBOs in Scandinavia from 2010 to 2016. Using a similar time window of [-1 : +2], Foldager and Mølbak conclude that SBOs perform less effectively than PBOs. This study utilizes OLS and a Wilcoxon signed-rank test to assess potential inferior performance in SBOs. Additionally, a driver study is performed on the SBO sample, using OLS-based multiple linear regression to identify drivers of operational value creation in SBOs. The findings suggest that CEO replacement significantly bolsters operational performance in SBOs, while fund-level industry specialization demonstrates statistical significance for superior operational performance (Foldager & Mølbak, 2020). Nonetheless, this study also relies primarily on database-extracted financial data.

4.3.1 Summary of SBO Literature

There seems to be no consistency across conclusions in the literature on SBOs. The key findings in existing literature are displayed below.

Author & Year	Sample	Time series	RQ	Key Findings
Bonini, 2015	EU	[-1:+2]	✓	SBOs significantly underperform PBOs in operating performance. SBOs exhibit a higher NIBD/EBITDA ratio. SBO activity is argued to be determined by debt market sentiment
Wang, 2012	UK	[-1:+3]	✗	SBOs do not enhance the target company's operational efficiency. SBOs demonstrate significantly improved performance in EBITDA/FA, while PBOs yield higher profitability in terms of ROA
Freelink & Volosovych, 2012	UK	[-1:1]	✓	SBOs demonstrate significantly inferior performance on operating metrics. Returns for SBOs are considerably lower than for PBOs
Arcot et al., 2013	US	[0:+6]		PE funds are highly likely to engage in exit or acquisition activities when faced with pressure to sell or buy, due to the inherent investment and divestment periods. Pressure impacts valuation
Plagborg-Møller & Holm, 2017	UK	Exit year		Better-performing portfolio companies are more likely to opt for IPOs as an exit route, Operating performance, company size, and market conditions have a significant impact on exit choice
Degeorge, Martin and Phalippou, 2015	Global	[-1:+3]		In general, late SBOs generate negative NPV to LPs. SBO transactions between PE firms with complementary skill sets generate significantly higher returns than between firms with similar skills
Achleitner & Figge, 2014	US & EU	[-1:+1]	✗	SBOs offer equivalent returns and exhibit similar operational performance to PBOs. SBOs displaying 28%-30% higher leverage, measured in NIBD/EBITDA
Sousa & Jenkinson, 2015	EU	Holding period		SBOs are more probable when the equity market exhibits a pessimistic outlook, and SBOs are more likely late in the fund's lifecycle
Skibsted & Thelin, 2018	DK, SE & NO	[-1:+2]	✓	SBOs significantly underperform PBOs on abnormal operating profitability measures EBITDA-margin and EBIT-margin. SBOs exhibit lower operating performance on EBITDA- and sales growth. Lastly, SBOs increase the debt-multiple levels more than PBOs
Foldager & Mølbak, 2020	Scandinavia	[-1:+2]	✓	SBOs exhibit inferior operational performance compared to PBOs. CEO replacements boost operational performance in SBOs, while industry specialization shows statistical significance concerning superior operational performance.

RQ denotes research question 1; SBOs exhibit inferior operational performance relative to PBOs.
✓ denotes the authors find statistically significant support for inferior operational performance in SBOs relative to PBOs
✗ denotes the authors find no statistically significant support of inferior operational performance in SBOs relative to PBOs

Table 4.2: Key findings on SBOs

4.4 Synthesizing Findings About Drivers of Performance in SBOs

SBOs often evoke a sense of skepticism. After a PE firm has deployed its strategic methods, the question arises: how can a subsequent financial sponsor replicate these strategies to deliver exceptional value to LPs? Despite these doubts, the growth trajectory of SBOs remains constant. This section aims to provide a synthesized overview of the examined SBO literature, creating a clear and comprehensive summary of main research topics, findings, agreements, and disagreements. This consolidation focuses on the drivers identified in the literature, grouping different researchers and their findings concerning each driver. The field of research focused on SBOs encompasses an extensive range of aspects that might significantly influence operational performance:

- Value Creation and Performance of SBOs
- Dry Powder and Buy Pressure
- Sell Pressure
- Complementary Skills

- Specialization
- CEO Replacement
- Private Equity Firm Fize
- Lead Partner Experience
- Timing of Capital Markets and Liquidity Needs

Value Creation and Operating Performance in SBOs

The points enumerated above help explain why PE firms engage in SBOs. Yet, the fundamental inquiry pertains to the value-creation attributes of SBOs. Given the confidential nature of PE, various methods are employed to assess value creation. A significant portion of the literature scrutinizes value creation through operating financial metrics. The central focus of the literature on SBOs, to a certain degree, investigates returns to investors. At one end of the spectrum, findings indicate that SBOs underperform PBOs. For example, the cash multiple of SBOs stands at 2,34 for every dollar invested versus 2,76 in PBOs—equating to a differential of 18% (Degeorge et al., 2015). Reasons for the underperformance of SBOs are linked to a reduced likelihood of extraordinary returns, along with variances in characteristics such as the size, leverage, and experience of the acquiring PE firm. SBOs influenced by the dry powder effect have been observed to underperform compared to other buyouts (Arcot et al., 2013; Jenkinson & Sousa, 2015).

4.4.1 Dry Powder and Buy Pressure

PE funds operating within a defined lifespan have been studied in the context of SBOs. A widely accepted belief points to the emergence of the principal-agent problem as the fund's investment period nears completion. Research suggests GPs initially align with LPs but shift towards spending dry powder on less valuable SBOs as the period ends. This trend towards reduced leverage GPs use in late-stage SBOs has been observed. This behavior, influenced by buying pressure, can escalate transaction values (Arcot et al., 2013). Thus, financial sponsors' decisions are likely influenced by the prevailing incentive structures. The combination of buying pressure and dry powder can erode investor value, with late buyout underperformance found to be 0,3 times lower than other buyouts (Degeorge et al., 2015).

Table 4.3: Key Findings on Buy Pressure

Author & Year	Sample	Hypothesis	Sig.	Key Findings
Wang, 2012	UK	Buy pressure	✓	SBOs executed under buy pressure exhibit inferior performance relative to other buyouts
Arcot et al., 2013	US & EU	Buy pressure	✓	PE funds are more likely to engage in SBOs under pressure. Pressure to buy leads to a higher valuation of the target

Sig. denotes whether key findings are supported by statistical significance at a 5%-level.
✓ denotes the authors find statistically significant support for key findings
✗ denotes the authors find no statistically significant support for key findings

4.4.2 Sell Pressure

Funds approaching the end of their divestment phase often face a challenging predicament. There may still be untapped potential within the portfolio company, including low-hanging fruits yet to be harvested, but the fund's

limited lifespan necessitates a swift exit. This leaves room for the SBO buyer to capitalize on the remaining growth prospects. Under such circumstances, an SBO becomes increasingly likely (Arcot et al., 2013). The likelihood of an SBO increases even further when a portfolio company has been held for an extended period, and if the PE firm launches a follow-up fund within two years of the portfolio company's sale, the odds of choosing an SBO exit strategy rise by 22% (Wang, 2012).

Table 4.4: Key Findings on Sell Pressure

Author & Year	Sample	Hypothesis	Sig.	Key Findings
Wang, 2012	UK	Sell pressure	✓	The probability of an SBO exit increases when a portfolio company has been held for an extended period
Arcot et al., 2013	US & EU	Sell pressure	✓	SBOs become increasingly likely when the selling fund is under pressure from fund closing
Arcot et al., 2013	US & EU	Sell pressure	✓	In SBO transactions with pressured buyers and sellers, the seller has the most bargaining power, as the buying fund is desperate to release dry powder to secure management fees

Sig. denotes whether key findings are supported by statistical significance at a 5%-level.
✓ denotes the authors find statistically significant support for key findings
✗ denotes the authors find no statistically significant support for key findings

4.4.3 Complementary Skills

The concept of complementary skills is evaluated with the financial sponsor of a portfolio company. High returns are significantly linked to instances when the subsequent PE fund possesses skills that enhance those of the initial sponsor, creating a synergistic effect (Degeorge et al., 2015). Diverse focuses, capabilities, and complementary skills among PE funds may include:

- Margin growth versus sales growth emphasis
- Operational efficiency improvements versus financial management focus
- Adoption of regional versus global strategies

Such skills can foster efficiency enhancements during both PBO and SBO phases (Wang, 2012). For example, the pairing of a PBO lead partner with a financial background and an SBO lead partner with a consultancy background can positively impact the SBOs performance (Degeorge et al., 2015). Research by Acharya et al. (2011) suggests a positive correlation between complementary skills at the lead partner level and operational performance, as well as deal value. However, a case study by Achleitner et al. (2014) presents an alternative perspective, indicating that operational performance improvements can be achieved absent complementary skills and capabilities between buyer and seller.

Table 4.5: Key Findings on Complementary Skills

Author & Year	Sample	Hypothesis	Sig.	Key Findings
Achleitner & Figge, 2012	Case study	Complementary skills		Operational performance improvements are achievable, even if the buyer does not possess skills and capabilities different from the seller
Acharya et al., 2013	UK & EU	Complementary skills	✓	Complementary skill sets at the lead partner level are correlated with operating performance and deal performance
Degeorge, Martin and Phalippou, 2015	Global	Complementary skills	✓	When buying and selling lead partners have complementary skill sets SBOs outperform other buyouts

Sig. denotes whether key findings are supported by statistical significance at a 5%-level.
✓ denotes the authors find statistically significant support for key findings
✗ denotes the authors find no statistically significant support for key findings

4.4.4 Specialization

In the realm of PE, specialization can confer a competitive advantage. Expertise, experience, and deep industry knowledge can be an appealing proposition for PE funds exploring investment opportunities. Firms demonstrating industry specialization tend to generate abnormal returns of 8.5% relative to non-PE-backed counterparts, although buyout specialization exerts minimal systemic influence on portfolio companies' growth and profitability (Cressy et al., 2007). Viewed from the lens of deal origination, industry specialization does not significantly affect the likelihood of a PE fund participating in an SBO (Arcot et al., 2013). Comparing specialized and generalist PE funds, (Grüner & Marburger, 2022) discovered that industry-specialized PE funds generate profits 7.5% higher than buyouts backed by generalist funds. They also observed a positive association between industry specialization and the Multiple on Invested Capital (MoIC) ratio. However, no significant influence on revenue and EBITDA growth was detected (Grüner & Marburger, 2022).

Table 4.6: Key Findings on Specialization

Author & Year	Sample	Hypothesis	Sig.	Key Findings
Cressy et al., 2007	UK	Industry specialization	✓	Industry-specialized PE funds, on average, generate an abnormal return of 8.5% compared to non-PE-backed firms.
Cressy et al., 2007	UK	Buyout specialization	✗	Buyout specialization has minimal systematic effect on growth and profitability.
Arcot et al., 2013	US & EU	Industry specialization	✓	Industry specialization has no significant impact on the probability of a PE fund engaging in an SBO.
Bruining et al., 2018	France	Industry specialization	✓	Industry specialized funds yield 7.5% higher profits compared to buyouts backed by generalist PE funds.
Gruener & Marburger, 2022	US, EU & UK	Industry specialization	✗	Industry specialization has a positive connotation with the MoIC ratio, while results for revenue and EBITDA growth are mixed.

Sig. denotes whether key findings are supported by statistical significance at a 5%-level.
✓ denotes the authors find statistically significant support for key findings
✗ denotes the authors find no statistically significant support for key findings

4.4.5 CEO Replacement

Within the sphere of PE, CEO replacement and incentive-based remuneration represent significant strategies to align the objectives of management and shareholders, as previously highlighted in this paper. Despite the

considerable interest in PE research, the scholarly consensus concerning the influence of managerial replacements on operational performance remains unsettled. In this context, two notable studies focusing on LBOs warrant discussion. Gong and Wu (2011), analyzing a US-based sample of LBOs, found a CEO turnover rate of 51% within the two-year post-LBO period. This study further elucidates that the propensity for CEO turnover amplifies with high agency costs and substantial CEO entrenchment. Poor-performing CEOs are more prone to replacement, with factors such as free cash flow, leverage, and CEO entrenchment contributing significantly to the CEO replacement decision. Guo et al. (2009) delve into the consequences on performance, determining that companies generate an increased return on sales and return on assets when a CEO replacement occurs within one year after the LBO transaction.

Table 4.7: Key Findings on CEO Replacement

Author & Year	Sample	Hypothesis	Sig.	Key Findings
Gong & Wu, 2011	US	CEO replacement	✓	Significant increase in the probability of CEO turnover if the company has high agency costs. CEO turnover of 51% within two years of LBO announcement
Guo et al., 2011	US	CEO replacement	✓	Post-LBO companies exhibit greater cash flow performance when the CEO is replaced in the first two years post buyout

Sig. denotes whether key findings are supported by statistical significance at a 5%-level.
✓ denotes the authors find statistically significant support for key findings
✗ denotes the authors find no statistically significant support for key findings

4.4.6 Private Equity Firm Size

Limited research explores the relationship between PE firm size and operational performance. Notably, firm size and human capital significantly impact investment opportunities, with a growing preference for small-to-mid-sized companies due to potential returns and less competition. S. N. Kaplan and Schoar (2005) identify a concave relationship between fund size and performance, indicating decreasing returns to scale for larger funds, despite higher public market equivalent (PME). Yet, when funds become excessively large, performance declines. Conversely, Humphery-Jenner (2012) suggests larger firms can more easily implement operational improvements, reflected in higher Internal Rate of Return (IRR). Investments in top quartile portfolio companies by size yield an IRR of 5.2%, compared to -2.9% for the bottom quartile. Contradicting these findings, Harris et al. (2014) and Lopez-de-Silanes et al. (2014) found no significant correlation between buyout fund size and performance. They observed a negative correlation between IRR and investment multiples related to capital commitments. The smallest quartile of buyout funds exhibited the poorest performance. Additionally, Lopez-de-Silanes et al. (2014) discovered diseconomies of scale related to the number of simultaneous deals a buyout fund undertakes.

Table 4.8: Key Findings on Private Equity Firm Size

Author & Year	Sample	Hypothesis	Sig.	Key Findings
Kaplan & Schoar, 2005	US	Size and fund performance	✓	When PE funds become very large, fund performance declines.
Humphery-Jenner, 2012	US	Size and performance	✓	Operational improvements are easier to implement in larger firms. Top-quantile targets yield an IRR of 5.2%, while bottom-quantile companies yield an IRR of -2.9%.
Harris, Jenkinson, & Kaplan, 2014	US	Size and fund performance	✗	No significant relationship between fund size and performance. IRR and investment multiples are negatively related to capital commitments.
Lopez-de-Silanes, Phalippou, & Gottschalg, 2014	Global	Size and fund performance	✓	No relation between fund size and returns. Diseconomies of scale are related to the number of simultaneous deals being undertaken.

Sig. denotes whether key findings are supported by statistical significance at a 5%-level.
✓ denotes the authors find statistically significant support for key findings
✗ denotes the authors find no statistically significant support for key findings

4.4.7 Lead Partner Experience

The influence of lead partner experience on operational performance has been the subject of numerous scholarly investigations. Cumming and Waltz (2010) examine this relationship and find that team diversity, encompassing education, professional experience, and years of experience outside PE, generally contributes to higher returns. Their study also scrutinizes the GP effect, the concept that lead partner experience affects returns. Empirical evidence reveals that acquisition experience of buyout firms indeed impacts buyout performance, with the GP effect favorably influencing returns. Supporting these findings, Acharya et al. (2011) offer evidence that the superior performance of large PE firms partially arises from differences in human capital or skills at the lead partner level. Amess and Wright (2013), meanwhile, shifts focus from returns to operational performance of portfolio companies in the first three years post-LBO. The researchers discover statistically significant support for the positive effect of lead partner experience on operational value creation. Most notably, the most substantial improvements occur within the first two years of ownership, suggesting PE firms employ their experience to drive organizational and strategic changes post-LBO (Amess & Wright, 2013).

Table 4.9: Key Findings on Lead Partner Experience

Author & Year	Sample	Hypothesis	Sig.	Key Findings
Loos, 2006	US & EU	Lead partner experience	✓	The GP effect positively influences buyout returns.
Acharya et al., 2013	UK & EU	Lead partner experience	✓	The superior performance of some PE firms is partly driven by differences in human capital or skill factors at the lead partner level.
Alperovych, Amess, & Wright, 2013	UK	Lead partner experience	✓	Lead partner experience positively influences operational value creation, with the most significant improvements within the first two years of the LBO-transaction.

Sig. denotes whether key findings are supported by statistical significance at a 5%-level.
✓ denotes the authors find statistically significant support for key findings
✗ denotes the authors find no statistically significant support for key findings

4.4.8 Market Timing

The choice of exit route appears to be largely influenced by prevailing market conditions. High-performing equity markets often prompt PE funds to divest through an IPO. In contrast, SBOs become more prevalent in periods characterized by subdued equity markets and low debt market spreads (Achleitner & Figge, 2014; Jenkinson & Sousa, 2015; Wang, 2012). Exits via IPO are typically associated with favorable equity market conditions and improvements in operational performance. In such contexts, studies suggest that a PE fund's decision to divest a high-performing portfolio company through an SBO may signal expectations of a market downturn (Plagborg-Møller & Holm, 2017). These researchers further argue that PE firms must instigate operational improvements in their portfolio companies to achieve superior returns. The existing literature concurs that the states of debt and equity markets significantly influence the choice of exit strategy.

Table 4.10: Key Findings on Market Timing

Author & Year	Sample	Hypothesis	Sig.	Key Findings
Achleitner & Figge, 2011	US & EU	Market timing	✓	When equity markets are "hot" and generating high returns, PE funds are more likely to divest through an IPO. Conversely, during periods of cold equity markets and low debt market spreads SBOs become more prevalent.
Wang, 2012	UK	Market timing	✓	SBOs are driven by the liquidity-based market timing motive.
Jenkinson & Sousa, 2015	EU	Market timing	✓	The choice between IPOs and SBOs depends heavily on the conditions in the debt and equity market.
Plagborg-Møller & Holm, 2017	France	Market timing	✓	PE firms must incorporate operational improvements in portfolio companies. A PE firm pitching a well-performing portfolio company is a sign of worsened market expectations.

Sig. denotes whether key findings are supported by statistical significance at a 5%-level.
✓ denotes the authors find statistically significant support for key findings
✗ denotes the authors find no statistically significant support for key findings

4.5 Summary of Literature Review

Private equity ownership has been demonstrated to enhance operational performance, necessitating operational value creation for delivering returns to LPs, rather than solely relying on market conditions (Guo et al., 2009; Jenkinson & Sousa, 2015; Jensen, 1989; S. Kaplan & Strömberg, 2009; Plagborg-Møller & Holm, 2017). SBOs, however, show mixed evidence in operational performance compared to PBOs. Some scholars find inferior performance and lower returns for SBOs (Bonini, 2015; Freelink & Volosovych, 2012), while others report similar operational performance between SBOs and PBOs, albeit with higher leverage in SBOs (Achleitner & Figge, 2014; Wang, 2012). Seven potential drivers of operational value creation in SBOs have been identified, including buy pressure, complementary skills, specialization, CEO replacement, PE firm size, and lead partner experience.

Pressure investing, leading to higher target company valuations, is associated with poorer operational performance (Arcot et al., 2013; Wang, 2012). Complementary skill sets at the lead partner level correlate with operating performance and returns (Acharya et al., 2011; Degeorge et al., 2015). Meanwhile, the results on industry specialization are mixed (Arcot et al., 2013; Cressy et al., 2007; Grüner & Marburger, 2022). High CEO turnover rate post-LBOs is associated with improved cash flow performance (Gong & Wu, 2011; Guo et al., 2009). Furthermore, the impact of fund size yields inconclusive results, with some authors suggesting decreasing returns to scale (S. N. Kaplan & Schoar, 2005; Lopez-de-Silanes et al., 2014), while others find no significant relationship between fund size and performance (Harris et al., 2014; Humphery-Jenner, 2012). Lead partner experience has been shown to positively influence operational value creation in the initial two years

post-buyout (Amess & Wright, 2013). Overall, most literature utilizes a multiple regression setup to test operational performance and its drivers, with a consensus around assessing performance within the first two or three years post-buyout due to early implementation of value creation incentives (Achleitner & Figge, 2014; Bonini, 2015; Freelink & Volosovych, 2012; Wang, 2012).

Identification of Research Gap

The literature demonstrates various answers to the question of inferior operational performance of SBOs relative to PBOs. Most studies are focused on the EU or US. Consequently, conducting a regression analysis on the mean and median values of operational performance measures may yield varying outcomes, contingent upon the geographic regions and countries represented in the data sample. Addressing the question of inferior operational performance of SBOs, the issue arises as Nordic transactions contribute minimally to mean and median values due to low transaction volume. Although certain research papers cover the Nordic region, the authors have identified a substantial opportunity for additional focused research on Scandinavia. The gap in research indicates a substantial potential for further research into the operational performance of SBOs and drivers of value creation in SBOs.

5.0 Formulating Hypotheses

In the following sections, hypotheses will be developed based on the knowledge and evidence accumulated until this juncture in the research. Drawing on the PE toolbox and engaging the influential literature in the review, it becomes possible to identify specific areas of interest and, thus, potential subjects for extended investigation and analysis. The research questions are reiterated below for the benefit of the reader:

Research Question 1

Do secondary buyouts exhibit inferior operational performance compared to primary buyouts?

Research Question 2

Which factors in the private equity toolbox are drivers of operational value creation in secondary buyouts?

In the context of the second research question, thorough deliberation has been accorded to the underlying hypothesis, as well as the justification for choosing specific theories, with the goal of PE toolbox and VCPs. PE funds aspire to accelerate growth and, consequently, generate value for investors. However, the procedure of value creation is far from simple. It necessitates thorough, concrete, and actionable strategies that senior partners can execute. Various methodologies exist for achieving VCPs, some of which are more explicit and quantifiable than others. The objective of this paper is to critically examine additional strategic actions that PE funds employ as tools for realizing VCPs. This subsection will briefly present the hypotheses to be examined, along with the underlying logic and reasoning for each. These hypotheses will provide the guiding framework for the analysis.

Operational Performance in SBOs vs. PBOs

The first research questions address whether SBOs exhibit inferior operational performance relative to PBOs. To cover this question, the following hypothesis is constructed.

H1: *SBOs exhibit inferior operational performance relative to PBOs*

The expectation of inferior operational performance is based on the contradictory results in existing literature. Some scholars find that SBOs significantly underperform PBOs on operating metrics (Bonini, 2015; Foldager & Mølbak, 2020; Freelink & Volosovych, 2012; Skibsted & Thelin, 2018). Conversely, other scholars find no statistical significance of underperformance in SBOs relative to PBOs (Achleitner & Figge, 2014; Wang, 2012). An interesting observation is that Freelink and Volosovych (2012) finds that SBOs demonstrate significantly inferior operational performance and lower returns than PBOs (Freelink & Volosovych, 2012). On the other

hand, Achleitner and Figge (2014) finds that SBOs exhibit similar operational performance to PBOs, except for displaying significantly higher leverage, measured by NIBD/EBITDA. Further, SBOs offer equivalent returns to PBOs. Circling back to Bonini, it remains unclear how a second financial sponsor can create value by exploiting the same value-creation mechanisms as the first sponsor. Nevertheless, Achleitner and Figge (2014) and Freelink and Volosovych (2012) present evidence that value creation mechanisms are somehow different from SBOs to PBOs, as a second sponsor can reap down low-hanging fruits not harvested by the first acquirer. Based on existing literature, it is expected that SBOs exhibit inferior operational performance relative to PBOs, which is expressed in hypothesis H1 addressing the first research question.

It is important to note that this thesis does not seek to assess returns to investors but solely addresses the question of inferior operational performance measured in operating metrics. Hence the paper does not seek to capture the effect of debt- and equity markets or other potential factors determining returns to investors.

Determinants of Operational Value Creation in SBOs

The second research question addresses drivers of operational performance, focusing solely on SBOs. The literature on drivers of operational performance identified several topics possibly affecting operational performance. The following sections will present different hypotheses addressing the second research question.

Pressure Investing

The pressure investing hypothesis is based on the findings in existing literature that pressure SBOs exhibit inferior operational performance relative to other buyouts (Wang, 2012). Furthermore, Arcot et al. (2013) finds that pressure investing leads to higher target valuations (Arcot et al., 2013). The hypothesis is formulated as follows.

H2(A): *Pressurized investments exhibit inferior operational performance relative to other SBOs*

It corresponds with traditional research, implying that pressured buying or selling impacts operational performance. The basis includes that pressure investing can trigger emotion-driven decisions, raising the chance of errors and potentially deteriorating performance. Due to time constraints under pressure, thorough due diligence might be compromised, risking oversight of essential operational elements. Similarly, hurried acquisitions or investments in such scenarios can inflate costs without adequate negotiation, negatively impacting profitability and performance. Moreover, this hypothesis is underpinned by the conceptual premise that PE firms might be inclined to utilize dry powder towards the end of a fund's lifecycle. This is often done to accrue management fees and carried interest. In such circumstances, these firms might be amenable to a lower IRR, reinforcing our initial supposition. Therefore, it becomes intriguing to examine whether SBOs, purchased after 3.5 years into the fund's vintage, experience inferior operational performance compared to other buyouts.

Complementary Skills

Existing literature demonstrates that operational performance in SBOs is correlated with complementary skill sets at the lead partner level (Acharya et al., 2011; Degeorge et al., 2015). The hypothesis is formulated as follows.

H2(B): *Complementary skills at the lead partner level have a positive influence on operational performance in SBOs*

Knowledge diversity from financial and consultancy backgrounds cultivates a comprehensive approach to oper-

ations and strategy. Combining financial expertise with operational knowledge may foster a holistic company understanding, enhancing performance. Complementary skills balance financial and operational considerations in decision-making, leading to improved performance. The blend of financial and consultancy skills promotes innovation, adaptability, and a resilient, performance-oriented culture. Lastly, the synergy from diverse skills often yields greater collective impact, improving operational performance.

Fund- and Industry Specialization

Existing literature presents mixed evidence on specialization and its effect on operational performance. Some scholars find that industry-specialized PE funds, on average, generate superior returns compared to generalist PE funds (Bruining et al., 2011; Cressy et al., 2007). On the other hand, Grüner and Marburger (2022) finds mixed results on sales growth and EBITDA growth (Grüner & Marburger, 2022). To address the question of fund specialization, the following hypothesis is formulated.

H2(C): *Specialized funds experience superior operational performance in SBO deals relative to generalist funds*

To delve deeper into the facet of industry specialization, an additional hypothesis is posited. This hypothesis considers whether SBOs exhibit superior performance if the acquiring PE firm has engaged in a minimum of three transactions within the primary sector of the SBO company.

H2(D): *Funds with industry experience exhibit superior operational performance in SBO deals relative to industry novice funds*

CEO Replacement

This hypothesis is based on the fact that PE firms often replace the CEO in anticipation of improved operational performance (Gong & Wu, 2011). Furthermore, Guo et al. (2009) finds an improved cash flow performance when the CEO is replaced. With this in mind, a hypothesis addressing CEO replacement and superior operational performance in SBOs is formulated.

H2(E): *CEO replacement has a positive impact on SBOs' operating performance*

CEO replacement is incorporated as a potential determinant based on the following justifications. Fresh leadership often ushers in innovative perspectives and strategic visions. These newly appointed executives may unearth overlooked opportunities and implement underestimated strategies, fostering operational enhancement (Gong & Wu, 2011). Their unique experiences and expertise could fortify decision-making and elevate the overall performance of SBOs. New management can also catalyze efficiency and productivity advancements. By introducing optimized operational procedures or policies, they can streamline operations, reduce costs, and boost performance. Additionally, management change can rejuvenate and refocus the organization. A fresh CEO could potentially instigate a transformative culture shift, positively affecting employee motivation and productivity. The points made are equivalent to those in the literature, making the hypothesis intriguing to investigate on the sample gathered in relation to this thesis.

Fund Size

The academic discourse surrounding the correlation between fund size and operational performance remains largely unresolved. Several researchers have found that as funds burgeon significantly, a subsequent depreciation in fund performance ensues, leading to diseconomies of scale concerning the volume of deals undertaken by the

PE fund (S. N. Kaplan & Schoar, 2005; Lopez-de-Silanes et al., 2014). The hypothesis related to fund size is formulated as follows.

H2(F): *Fund size has a positive influence on operating performance in SBOs*

The bigger is better principle suggests that larger PE funds have access to substantial resources, enabling investments in technology, infrastructure, or personnel to enhance performance. Large funds may use their extensive experience to optimize operations, enhance efficiency, and facilitate market expansion. They can leverage extensive industry networks for partnerships, customer acquisition, and superior supplier sourcing, improving efficiency and performance. Furthermore, they can implement robust corporate governance practices, improving decision-making, risk management, and operational effectiveness. Lastly, large funds may have better access to debt capital markets, facilitating low-cost financing for acquisitions or improvements, leading to higher profitability and enhanced performance.

Lead Partner Experience

The literature review presents conclusive results that lead partner experience positively influences operational performance (Acharya et al., 2011; Amess & Wright, 2013). This assertion is predicated on the belief that lead partners with more experience, combined with profound industry insights, are adept at overcoming sector-specific impediments. Such expertise facilitates judicious decision-making that ultimately contributes to the success of portfolio companies.

H2(G): *Lead partner experience positively influences operational performance in SBOs*

This hypothesis is furthermore supported by the argument of Gilligan and Wright (2020) that experienced lead partners have access to a more attractive deal flow. Furthermore, experienced partners may have extensive networks that unlock new growth opportunities and bolster operational performance. Furthermore, investment expertise could help identify lucrative opportunities for portfolio companies. Having traversed multiple economic cycles, experienced lead partners may hold superior risk management skills to protect companies from potential dangers. Their leadership guides management teams in decision-making and overcoming challenges, ultimately improving performance. Lastly, a proven track record may boost investor confidence, attracting increased investments and promoting financial stability and growth.

6.0 Methodology

The methodology implemented to address the research questions of the thesis forms the subject of this chapter. Table 6.1 below provides a summary of the main methodological decisions. Detailed explanations of these choices ensue in the subsequent subsections.

Table 6.1: Breakdown of Key Methodological Considerations

Topic	Description
Data Sample	A total of 103 SBOs and 147 PBOs from 2005 to 2020 have been collected and analyzed.
Financial Data	All necessary financial data have been hand-collected from annual reports.
Financial Metrics	9 KPIs for each SBO and PBO have been evaluated. Comparison with peer groups, determined by the industry matching principle, allows for the measurement of abnormal performance relative to industry peers.
Normalization	Income statement items are normalized, adjusting for changes in fiscal years.
Winsorization	All KPIs are winsorized at a 5% level, adjusting for extreme outliers
Time Series	Selected KPIs are analyzed from year [-1 : +2] surrounding the transaction
Statistical Testing	The research questions are addressed using OLS regression analysis on abnormal operating performance (AOP) measures.

6.1 Constructing a Representative Data Sample

Essential to the empirical testing of operational value creation is the construction of a representative sample. As the methodological approach for this thesis is influenced by techniques from existing literature, the construction of a dataset conforming to an i.i.d[1] assumption becomes a necessity for valid testing (Linton, 2019).
The dataset consists of two groups: a treatment group and a comparison group, with the former further divided into SBOs and PBOs. This thesis investigates the operational performance in Nordic SBOs and PBOs from 2005 to 2020. Thus, in agreement with existing literature, the abnormal operational performance (AOP) has been evaluated in the years [-1 : +2] surrounding the transaction. Benchmarking of financial metrics in the treatment groups against ten industry clusters is undertaken, following the industry matching principle. These

[1] i.i.d. denotes Independent and Identically Distributed, which is a fundamental assumption in many statistical models.

clusters are based on Fama & French's 10 industry classification system (French, 2023), leading to the creation of a comparison group composed of 172 industry peers.
Detailed information about global M&A transactions from repositories such as Mergermarket and Zephyr has been employed to identify Nordic transactions. To prevent duplication, each transaction has been cross-verified, particularly those that may have arisen in the context of syndicate deals. The construction of the treatment group is fundamentally reliant on the SBO sample, whereas the derivation of the PBO sample is contingent on the transaction years and the Fama & French 10 (FF10) industry clusters inherent to the SBO sample.

6.1.1 Identifying the Treatment Group

Mergermarket and Zephyr, both equipped with adaptable query capabilities for transaction analysis, serve to filter and compile Nordic PE transactions. The adopted search strategy focuses on completed transactions in Denmark, Sweden, and Norway. Only transactions implicating a majority stake ($> 50\%$) are considered, a criterion derived from the understanding that PE funds with minority stakes in syndicates typically assume less active ownership roles in portfolio companies (Vinten, 2007). Institutional buyouts exclusively constitute the search strategy, thereby excluding management buyouts, capital increases, divisional buyouts, spin-offs, and joint ventures.

Establishment of the SBO Sample
Buyouts at secondary, tertiary, quaternary, and quinary levels, among others, are classified as SBOs within the data sample. Conversely, if a portfolio company is publicly listed via an IPO and subsequently delisted, it is categorized as a PBO. Applying these criteria in Mergermarket and Zephyr yields a sample of 311 SBO transactions after adjusting for duplication and exclusion of minority stake deals. Each transaction underwent rigorous cross-verification against DVCA, SVCA, NVCA[2], PE fund websites, and S&P Capital IQ to affirm its validity. This procedure was instrumental in identifying potential discrepancies and ensuring comprehensive inclusion of all pertinent transactions. The subsequent application of seven specific criteria resulted in a refined sample of 311 transactions.

Table 6.3: Selection Criteria for the Initial SBO Sample

Number	Criteria
(1)	Target company is based in Denmark, Sweden, or Norway
(2)	Both acquirer and seller are identifiable private equity funds
(3)	Available consolidated statements for years [-1 : +2] around transaction
(4)	Holding period for the target exceeds 2 years
(5)	Primary sector of the target is not the financial sector
(6)	Target is neither a financial nor an infrastructure asset
(7)	Target does not declare bankruptcy during the SBO holding period

Transactions involving pension funds, asset management firms, venture capitalists (VCs), and other institutional investors on either the acquiring or selling side have been excised from the sample. VCs, despite sharing characteristics with PE funds, primarily concentrate on early-stage growth investments, unlike PE funds, which

[2]The trade association for active owners in Denmark, Sweden, and Norway, respectively.

orient towards more mature and stable companies (Stowell, 2018). Financial institutions have been omitted from the target list due to the distinct structure of financial statements compared to companies in other sectors. Moreover, financial assets like funds, infrastructure assets, and real estate funds have been eliminated from the sample. This decision aligns with the understanding that these assets undergo unique business and economic cycles, potentially skewing values in financial data. Constraints regarding available consolidated financial statements have led to excluding observations post-2020, eliminating 12 observations from the sample. The criteria-guided extraction of observations is detailed below.

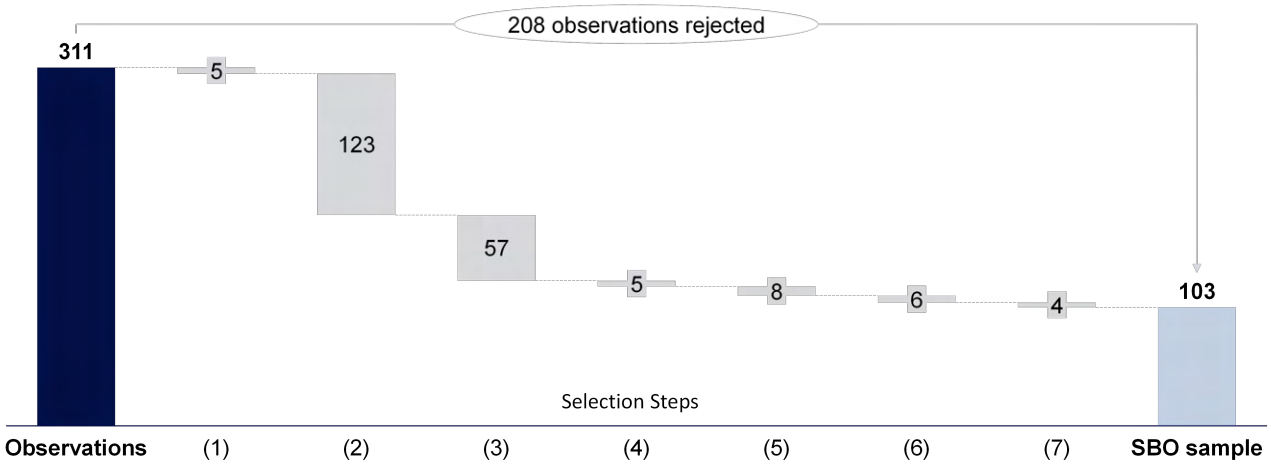


Figure 6.1: Selection Steps Leading to Final SBO Sample

The exclusion of 123 observations resulted from neither acquirer nor the seller being identified as PE funds. Within these transactions, 14 are categorized as trade sales, 23 as PBOs, and 7 as MBOs. Typical financial sponsors in the excluded transactions are pension funds, asset management firms, or VCs. The availability constraint on consolidated financial statements led to the exclusion of 57 observations. The initial sample is reduced from 311 observations to 103. This reduction corresponds to the exclusion of 208 observations from the SBO sample. Only those transactions for which data across all nine KPIs is available are incorporated into the sample. The specific definition of these KPIs will be provided in subsequent sections of this chapter. See appendix I for a comprehensive overview of transactions in the SBO sample.

Establishing the PBO Sample

The PBO sample is derived based on the FF10 classifications of the observations in the SBO sample. Initially, approximately 2200 PBO transactions from Denmark, Norway, and Sweden from 2005 to 2020 were extracted from Mergermarket and Zephyr. Based on the SBO sample, the inclusion of PBOs depends on two factors: their FF10 industry classification and the temporal proximity of the transactions, defined as $\pm$ 1 year surrounding the SBO transaction. For instance, an SBO transaction completed in 2013, with healthcare as the FF10 industry classification, would warrant the inclusion of all PBOs in the healthcare industry $\pm$ 1 year from 2013. This method aims to eliminate selection bias by including specific PBOs, removing the potential to select only high or low performers. It is believed that this method bolsters the potential for an unbiased result and closely reflects the underlying population, provided the sample size is large. See appendix J for a comprehensive overview of transactions in the PBO sample.

6.1.2 Comparison Group and Matching Method

To ensure accurate empirical testing of operational performance in SBOs and PBOs, it is imperative to consider time- and industry-specific effects that may influence the sample. The treatment group is composed of observations derived from a time series spanning over a duration of 15 years, encapsulating heterogeneous industries, each distinguished by a unique set of fundamental drivers that exert significant influence on operational performance.

Two methods to account for industry- and time-related effects are recognized in the academic literature: the direct comparison method and the control group comparison method. The direct comparison method, also known as the subsequent principle, compares the initial buyout directly with the subsequent one. The findings of Holm and Plagborg-Møller show that PBOs that end up becoming SBOs can be identified as portfolio companies not realizing expected sales growth and margin expansions to be IPO candidates (Plagborg-Møller & Holm, 2017). Consequently, applying the subsequent method would sort out the best-performing PBOs, thus creating a downward-biased SBO sample. On the other hand, the control group comparison method includes two approaches: the direct matching principle and the industry matching principle. The direct matching principle, though labor-intensive and prone to selection bias, enables a granular comparison by aligning the financial metrics of the treatment company with selected peers sharing similar criteria (S. Kaplan, 1989; Wang, 2012). For a more comprehensive examination of whether SBOs underperform PBOs in the Nordics, the industry matching principle was favored. This method, by allowing all PBOs and SBOs into the analysis, provides a more reliable measure of general operational performance (Wang, 2012). Here, each treatment company is matched with a corresponding comparison group within the same industry, ensuring similar industry characteristics. The financial metrics from the treatment company are then compared to the median values of the corresponding comparison group. Although less precise than the direct matching approach, the industry matching method mitigates systematic risk factors and handles variability in financial metrics over time. Based on these considerations, the industry matching approach was utilized to construct the comparison groups. Figure 6.2 illustrates the chosen method and the difference between the mentioned approaches.

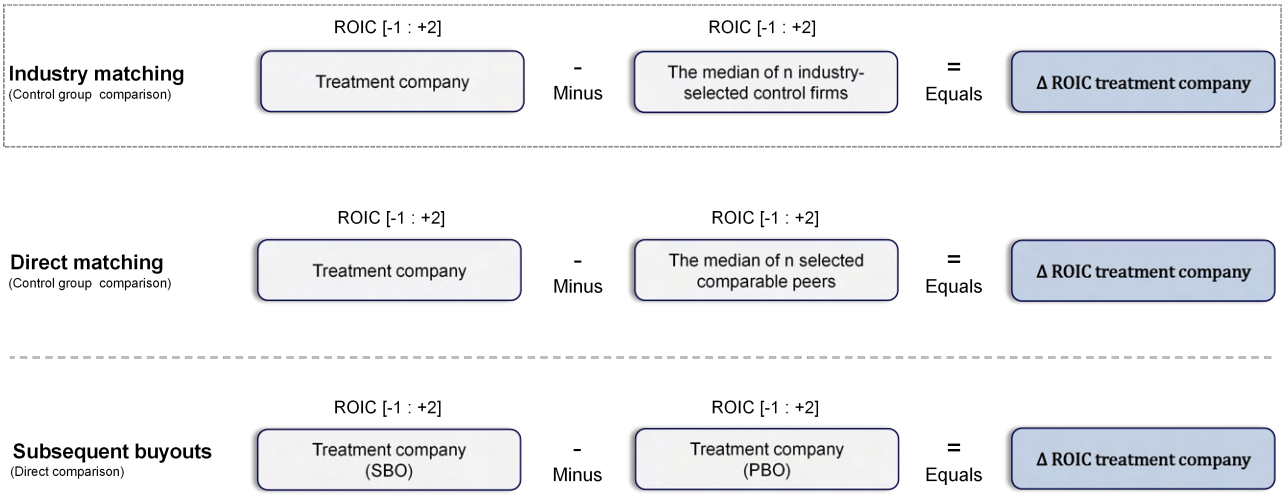


Figure 6.2: Calculation of Abnormal Operating Performance

Source: Authors creation

Establishment of the Comparison Group
The comparison group, based on the FF10 industry classifications and industry distributions in the SBO and PBO sample, was derived using the S&P Capital IQ company screening tool. The initial screening focused on publicly listed Nordic companies due to the availability of data from 2005 to 2020 and superior data quality (Plenborg & Kinserdal, 2021). However, due to insufficient sample sizes in certain industry categories, a selection of private companies was included to augment the sample size. This necessitated additional data validation, which was achieved using annual reports. Appendix H provides a comprehensive breakdown of the FF10 classifications and SIC codes. The screening tool produced a smaller comparison group within the seventh category (retail). This was mainly because of the limited number of publicly listed companies and those lacking consolidated financial statements on the S&P Capital IQ platform. As a result, we combined the retail category with the consumer staples category. See appendix K for a comprehensive overview of the comparison group.

6.2 Gathering Financial Data

Initially, the collection of financial data involved sourcing information from established databases such as Valu8, S&P Capital IQ, and Orbis. However, a noticeable incongruity emerged between the financial metrics reported in these databases and the metrics found in the company's annual reports. The discrepancy necessitated a significant methodological shift. Rather than relying on inconsistent database-sourced metrics, a decision was taken to manually extract data from the respective annual reports of each firm in the treatment groups, in contrast to existing literature. This process, referred to as hardcoding, ensured the highest level of data reliability and precision, but it also substantially increased the time and effort required for data collection. In this context, it is plausible to contend that manual data extraction may introduce typing errors. To mitigate this risk, a quality assurance process was instituted. Both authors were involved in the data extraction process. After this, a thorough review was undertaken whereby the hardcoded data were cross-verified against the respective annual reports from which it had been extracted. This methodical approach was designed to eliminate any potential typing errors.

The challenges of extracting accurate financial data from a database can be traced back to the intricate corporate structures that typify PE funds and their portfolio companies. In these entities, debt is often obtained across one or even multiple holding companies, as illustrated in figure 2.2, which depicts the typical structure of PE funds. Particularly problematic was the NIBD measure when extracted from databases, which was consistently underreported. This discrepancy was most likely due to the layered debt structure inherent to these firms, which standard database metrics may not fully capture. A detailed example, to be provided in a later subsection, will further illustrate this issue.

The annual reports of Danish companies were collected through the central business registry, CVR.dk. Challenges arose when collecting Swedish annual reports due to charging fees. This issue was circumvented by utilizing Allabolag.se, a platform that offered free access to annual reports from 2011 onwards. In relation to Norwegian data, the authors leveraged Brønnøysundregistrene, the corporate database for Norwegian firms. The data collection process for treatment groups contrasts with comparison groups, as highlighted in the section establishment of the comparison group.

6.3 Time Window of Measurement

The measurement time window selected for this study is [-1 : +2] surrounding the transaction, a selection commonly used in prior research. This interval allows for calculating change measures, with particular emphasis on the year preceding the transaction. Furthermore, the [-1 : +2] time window resonates with academic viewpoints suggesting that PE funds strive for immediate gains through implementation of VCPs, thus optimizing enterprise value (Achleitner & Figge, 2014; Bonini, 2015; Wang, 2012).

Evaluating performance within this window illuminates PE funds' short-term VCP execution, notably relevant in SBOs where operational enhancements may have been pursued by prior acquirers (Bonini, 2015; Wang, 2012). Research by Amess and Wright (2013) corroborates the efficiency of PE firms in initiating operational improvements during the initial ownership years, marking significant efficiency enhancements during the first two years. Even though the time window introduces some uncertainty, owing to holding periods frequently extending beyond two years, expanding the time series could lead to a substantial reduction in sample size, as the holding periods in the treatment group are typically less than three years. Moreover, financial metrics may see alterations due to strategic initiatives such as buy-and-build strategies or business model innovation. With these factors in mind, the study's timeline is intentionally designed to conclude in the second year post-transaction.

6.4 Identifying Dependent Variables

To adequately address the research questions, it is essential to analyze sample companies from a multi-dimensional perspective. Value, while often encapsulated in a singular number, is driven by an array of underlying factors. Thus, the investigation targets five key aspects of value creation: growth, profitability, return, efficiency, and leverage. These elements play a critical role in the detailed analysis of abnormal operating performance in SBOs compared to PBOs.

Growth

Growth remains a paramount determinant of operational value creation. Top-line growth strategies, defined in Chapter 3 and commonly implemented under PE ownership, influence exit valuation significantly (Capital Dynamics, 2014). This study employs a sales compound annual growth rate (CAGR) to gauge the portfolio company's ability to propel sales growth throughout the initial two years of the holding period. Using CAGR assists in minimizing biases introduced by extreme outliers tied to expansion measurements and size discrepancies among the companies in the treatment group. This selection aligns with the the literature review in chapter 4 (Achleitner et al., 2014; Bonini, 2015).

Notwithstanding, the sales CAGR metric might face scrutiny due to its failure to distinguish between organic and inorganic growth. Buy-and-build strategies, for example, could inflate sales CAGR artificially. Note that inorganic growth might not reflect genuine value creation if not accompanied by a corresponding rise in profitability and increasing cash flow. However, strategies incorporating buy-and-build remain crucial to the value-creation process in PE. Therefore, buy-and-build instances are included in the sample. To counteract the limitations due to a lack of clarity in differentiating organic and inorganic growth, profitability measures have been combined with the sales CAGR metric.

Profitability

The EBITDA margin expansion from [-1 : +2] is included as a dependent variable to measure profitability. By considering the change in the EBITDA margin, it is possible to assess whether the PE fund is able to improve the EBITDA margin in the first two years of the holding period. The inclusion of EBITDA is further supported by the importance of the metric in relation to valuation c.f. chapter 3. From a scholarly perspective, EBITDA is widely accepted as a comparative metric. Its utility lies in its ability to transcend variations arising from divergent tax policies, depreciation and amortization schedules, and capital structures, thereby enabling a more equitable comparison across diverse entities (Plenborg & Kinserdal, 2021).

Returns

In the present context, return diverges from the conventional understanding of investor returns via capital gains on the exit transaction, instead placing a focus on financial return measures. ROIC is included as a critical return measure. It serves as an essential metric for comprehensively evaluating a company's ability to create value for its shareholders. By demonstrating how effectively a company utilizes its invested capital to generate profits, ROIC provides a robust assessment of value creation. With invested capital in the denominator, ROIC enables comparisons devoid of influences from factors such as depreciation and amortization schedules, and tax considerations. Thus, it facilitates meaningful comparative analysis across companies operating in various industries (Plenborg & Kinserdal, 2021).

Further, ROE and ROA are integrated as return measures. ROE specifically appraises a company's total equity profitability, offering insights into the returns on equity. Conversely, ROA focuses exclusively on total assets, measuring efficiency in profit generation. Given that ROE and ROA place net income in the numerator, they are sensitive to financial expenses, depreciation and amortization, and taxes. EBITDA, on the other hand, strictly evaluates operating performance, excluding non-operating expenses and non-cash items. It provides a clearer perspective on a company's operating efficiency and profitability. Considering a trend of negative net income, return measures that include net income may display a downward bias due to non-operating items during the first two years following the transaction. This observation underscores the relevance of supplementing ROIC with ROE and ROA.

Return KPIs are implemented as expansion measures. For instance, changes in ROIC from the year before the transaction to two years afterward are considered. Consequently, the study evaluates the ability of PE funds to augment ROIC during the first two years of the holding period, in comparison to the median expansion measure of the control group.

Efficiency

Operational efficiency is assessed through two key ratios: Sales to Invested Capital (Sales/IC) and Free Cash Flow to Invested Capital (FCF/IC), which serve as dependent variables. The Sales/IC ratio demonstrates the effectiveness of a business in converting its invested capital into sales, providing a measure of capital efficiency. A higher ratio implies superior capital efficiency, indicating that the company can generate higher sales per unit of capital invested. This has a direct bearing on ROIC (Koller et al., 2020).

In the context of PE, where funds are expected to leverage an increased invested capital for growth acceleration, this ratio is crucial in measuring operational performance. Conversely, the FCF/IC ratio gauges the company's ability to generate free cash flow beyond its operating expenses and capital expenditures. Therefore, while the Sales/IC ratio indicates a firm's efficiency in translating invested capital into sales, the FCF/IC ratio measures how effectively sales translate into free cash flows. Together, these ratios provide a holistic insight into the operational and financial performance of a portfolio company.

In assessing expansion, these efficiency metrics are employed. For instance, Sales/IC is evaluated as the change

in Sales/IC from the year prior to the transaction to two years post-transaction. This measure helps to evaluate the ability of PE funds to enhance the Sales/IC ratio during the first two years of the holding period, compared to the median improvement of the corresponding control group.

Leverage

Leverage is recognized as a crucial component in the private equity toolbox, serving as an integral part of financial engineering strategies. For this reason, the ratios NIBD/EBITDA and NIBD/FA are incorporated as dependent variables.

The NIBD/EBITDA ratio is often included as a critical element in the covenants associated with bank debt. This ratio is a significant measure of financial leverage, as it evaluates the company's level of debt in relation to its operating income. The NIBD/FA ratio, on the other hand, provides an assessment of leverage relative to fixed assets, which might serve as collateral. It's important to note that the acceptable thresholds for the NIBD/FA ratio can vary widely across industries. Factors such as capital intensity and the conventional profitability of fixed assets within those sectors can influence these benchmarks (Plenborg & Kinserdal, 2021).

Leverage KPIs are also calculated as expansion metrics, helping to provide a comprehensive understanding of changes in companies' financial leverage.

6.5 Adjustments and Calculations of Financial Metrics

6.5.1 Normalizing Financial Statements

Significant challenges arise during the extraction of financial data. It has been documented that financial statements, following an acquirer's control over a target, fail to include the period preceding the transaction. Complications further arise as targets often alter their fiscal year during the transaction year, leading to financial statements that do not reflect a full fiscal year. These reports tend to focus on the period after the transaction, ignoring the financial data from the former owner. To rectify this situation, the fiscal year needs normalization to showcase an entire year of operations. For example, an income statement for the period from the end of June to the end of December represents merely six months of operations. Thus normalization in the context of this thesis is defined below.

$$\frac{\text{Line item in the income statement}}{n \text{ months reported}} \times 12 \tag{6.1}$$

Normalizing financial statements, though beneficial, does not factor in the potential for seasonality effects within specific companies or industries. Nevertheless, it aids in normalizing truncated or extended financial statements. Its application restricts solely to income statement line items, as using it for balance sheet items would be incorrect, given that a balance sheet encapsulates a company's financial position at a particular moment (Plenborg & Kinserdal, 2021).

Depreciation and Amortization (D&A) also undergo normalization, in alignment with the prevalent use of straight-line D&A. Conversely, only income statement items undergo normalization in the cash flow statement. The lack of normalization of investing and financing activities could potentially result in an inaccurate Free Cash Flow (FCF), while its application may introduce a bias, either upward or downward. The choice to normalize solely the income statement items in the cash flow statement is deliberate and a consequence of hardcoding financial data. Examination of the financial statements from all sample companies revealed substantial fluc-

tuations at the inception/change of PE ownership. These factors, therefore, demand rigorous scrutiny when assessing the accuracy and reliability of FCF measures.

6.5.2 Computing Return on Invested Capital (ROIC)

ROIC, an integral financial metric, indicative of a company's efficiency in deploying capital towards gainful investments. High ROIC generally signals proficient strategy execution and effective capital allocation, contributing to enhanced shareholder value (Koller et al., 2020). ROIC facilitates fair comparisons between companies across different industries, accounting for factors such as tax rates and financial leverage. However, ROIC is not without limitations, including possible variations due to differing accounting policies.

Implementing ROIC involves certain considerations. Within the scope of this thesis, deriving NOPAT directly from financial statements is impracticable, therefore the following formula serves as a stand-in (Plenborg & Kinserdal, 2021).

$$\text{NOPAT} = \text{EBIT} \cdot (1 - \text{tax rate}) \tag{6.2}$$

For NOPAT calculation, a corporate tax rate is required, determined by averaging the most recent OECD-reported rates from Denmark, Norway, and Sweden, which is the geographical scope of the thesis (OECD.stat, 2023).
The application of a uniform corporate tax rate of 21.5% throughout the sample, as opposed to effective tax rates, is necessitated by the limitations of the thesis. Invested capital, the denominator in the ROIC calculation, can be calculated via two methods: the operating and financing approach. Both should yield the same results (Plenborg & Kinserdal, 2021). However, including goodwill in invested capital presents complexities that demand further investigation.
Typically, ROIC would be benchmarked against the WACC to determine the Economic Value Added (EVA) (Plenborg & Kinserdal, 2021). However, this step is omitted in this study, acknowledging its importance but stating its exclusion due to the thesis's focus not being on single instances in the sample. Goodwill is the surplus of acquisition price over the book value of assets, often appearing on balance sheets following company acquisitions. Despite being considered a non-contributing item in cash flow analyses (Damodaran, 2007), its exclusion from invested capital can inflate ROIC significantly, especially in PE contexts primarily involving acquisitions and divestments. The potential of inflated operating numbers due to PE firms' strategies to maximize returns further skews ROIC measures. Given these considerations, the authors contend that including goodwill in invested capital provides the most accurate ROIC for benchmarking among PBOs, SBOs, and the comparison group.

6.6 Leverage Level

As reiterated, leverage is a crucial element of the VCPs within the financial engineering part of the PE toolbox. Establishing the critical considerations for the computation of leverage/debt-related measures is of importance. Net Interest-Bearing Debt (NIBD) gauges a company's debt level and is computed as the total of interest-bearing debt less cash and cash equivalents. NIBD is vital in the DCF valuation model, being subtracted from the enterprise value to determine equity value. Yet, this metric is not directly reported on the balance sheet, necessitating analytical computation. In the realm of PE, NIBD calculation involves several factors that must be considered:

- Quality of financial data

- Intra-group loans
- Shareholder loans
- Leases

Data collected from databases displayed low NIBD levels across both samples, underscoring the complexities of NIBD calculations introduced by the structure of PE funds. Primarily, financial statements must be consolidated at the group level, given that debt is frequently sourced from parent holding companies c.f. figure 2.2 on fund structure. Disregarding debt held by holding companies yields significantly lower NIBD values. Secondly, unconsolidated corporate structures compound NIBD computation further. To address this, researchers used an elimination approach to aggregate external debt from all group entities while eliminating financial assets to prevent double-counting of debt (Plenborg & Kinserdal, 2021). Finally, the calculation deducts group-level cash and cash equivalents to determine NIBD. The complexities are highlighted through NIBD computations at various levels for Inflight Services AB, illustrating the divergences if meticulous consideration is not applied.

6.6.1 Exemplifying Financial Data Quality

Inflight Service, a Swedish enterprise operating in the airline, airport retail, and cruise ship service sectors across the Nordic and Baltic regions, presents an interesting case for NIBD computation. In 2011, a NIBD calculation for Inflight Service Europe AB, using data from Capital IQ, returned a negative value of 1.1 mEUR. Contrasting, an analysis using hand-collected data from the annual reports yielded a notably different NIBD of 10.9 mEUR. The balance sheet for that year reflected an intra-group loan of 107.6m SEK and cash and cash equivalents amounting to 9.8 mSEK.

A detailed review of the management statement and accompanying notes in the annual report led to identifying Ifs Global AB as the parent company of Inflight Service Europe AB. Data manually collected from Ifs Global AB revealed long-term bank debt of 236 mSEK, short-term bank debt of 63m SEK, a long-term intra-group loan of 262m SEK, and a shareholder loan of 109 mSEK. Cash and cash equivalents stood at 47 mSEK. Consequently, the NIBD for Ifs Global AB was determined to be 58.5 mEUR.

A meticulous examination of the notes in the Ifs Global AB annual report disclosed that Inflight Service Holding AB functioned as the ultimate parent company of the group. In 2011, Inflight Service Holding AB carried long-term bank debt of 149 mSEK, short-term bank debt of 12 mSEK, an intra-group loan of 357 mSEK to Triton Masterluxco 2 S.a.r.l with a 10% interest rate, a shareholder loan of 119 mSEK, and cash and cash equivalents of 51 mSEK. After considering these factors, the NIBD for the ultimate parent company, Inflight Service Holding AB, was computed to be 65 mEUR.

Table 6.5: Steps to Derive Accurate Debt Measures

Company	Structure	Source	NIBD			NIBD / EBITDA		
			2010	2011	2012	2010	2011	2012
Inflight Service Europe AB	Subsidiary	Capital IQ	-3,2	-1,1	-1,9	-0,3x	-0,1x	-0,1x
Inflight Service Europe AB	Subsidiary	Annual Reports	5,5	10,9	6,7	0,5x	0,8x	0,5x
Ifs Global AB	Holding	Annual Reports	63,8	58,5	57,3	6,0x	4,5x	4,3x
Inflight Service Holding AB	Group Holding	Annual Reports	70,3	65,7	64,7	6,6x	5,0x	4,7x

All NIBD numbers are EUR millions

Intra-group Loans

This study acknowledges intra-group loans due to their prevalence in the portfolio companies' group structures, which employ transfer pricing practices. These practices, subject to change over time, are not adjusted yearly due to the scope of the thesis. Intra-group loans appearing on the balance sheet are recognized in the NIBD calculation, considering their potential to become future cash expenses and their role in achieving positive leverage, a critical aspect of PE. These loans follow OECD transfer pricing guidelines, maintaining the arm's length principle, wherein terms are consistent with market-level debt conditions (OECD, 2022).

Shareholder Loans

Regarding shareholder loans, this study acknowledges the debate around classification as debt or equity. Some might view these loans as an advanced form of equity financing, especially if subordinated to other debt forms. However, this study includes interest-bearing shareholder loans in NIBD, as these loans will eventually entail a cash expense that the company must repay with interest. Excluding these loans might lead to underestimating the company's financial leverage.

Leases

Lease recognition is another crucial aspect in NIBD calculation. According to IFRS 16, all leasing contracts should be capitalized as a leasing asset and liability, with the total equating to the present value of future lease payments in the contract (Plenborg & Kinserdal, 2021). Including leases in NIBD is justified on the basis that they bear interest. However, it poses a challenge as private companies are not legally mandated to disclose whether leases are operational or financial, potentially leading to the exclusion of leases not capitalized on the balance sheet.

In conclusion:

Definition 4: Net Interest-Bearing Debt (NIBD)

NIBD, in the context of this thesis, is defined as the total of long-term interest-bearing debt, short-term interest-bearing debt, intra-group loans, leases, and shareholder loans, minus cash and cash equivalents.

It represents the total debt of the company that has to be serviced by paying interest, considering liquid assets that could be used to instantly pay off some debt.

In mathematical terms, this can be represented as:

$$NIBD = Long\text{-}term\ Debt + Short\text{-}term\ Debt + Intra\text{-}group\ Loans + Leases + Shareholder\ Loans - Cash\ and\ Cash\ Equivalents$$

Winsorization of Data

Extreme outliers in both PBO and SBO samples distort results if not addressed appropriately. Outliers in financial statement analysis often fail to reflect the true measures or underlying fundamentals. As a consequence, all financial data in PBO, SBO, and industry peer samples have undergone winsorization to circumvent erroneous conclusions attributed to extreme outliers. The choice to employ winsorization is inspired by existing literature (Jenkinson & Sousa, 2015). Winsorization is a proven statistical technique for minimizing the impact of outliers, replacing extreme data values with designated percentile values within a dataset. In this specific study, symmetric winsorization at the 5% level has been implemented. This technique adjusts values falling below the 5th percentile and those exceeding the 95th percentile to their respective percentile values. This method reduces skewness and the influence of outliers at both ends of the distribution, thus maintaining the integrity of the overall data. This adjustment enhances analysis robustness, yielding a more reliable statistical estimate (Dixon, 1960).

6.7 Choice of Explanatory- and Control Variables

6.7.1 Explanatory Variables

This paper employs explanatory variables as dummy variables, each representing a unique hypothesis formulated within the study. In the first research question, a dummy variable functions to differentiate between SBOs and PBOs in the regression model: a value of 1 denotes an SBO transaction, whereas a value of 0 signifies a PBO transaction.

In the second research question, the explanatory variable of each hypothesis is represented through a corre-

sponding dummy variable. For example, in the CEO replacement hypothesis, a dummy variable is used to signify the occurrence of a CEO replacement within the first year (1) or no change in the CEO position (0). The variables of fund size and lead partner experience deviate from this pattern due to their distinct categorical variations, thus necessitating more than one explanatory variable. To address the inherent disparities in fund sizes and the varied experience levels of lead partners, empirical testing is conducted for each category within these variables. This method ensures that the unique nature of these variables is adequately accommodated.

All explanatory variables and respective sources for data collection are depicted in table 6.7, providing a full overview of the variables incorporated in the regression analysis.

Control Variables

The identification of control variables derives from prior literature, supplemented with variables believed to contribute to explaining the variance in regression models. The subsequent sections elucidate the selection of optimal control variables using AIC scores. The variables under consideration for further selection are as follows.

- EBITDA Margin $_{t-1}$
- Ln(Assets) $_{t-1}$
- Capital Structure $_{t-1}$
- Quick Ratio $_{t-1}$
- NWC/Sales $_{t-1}$
- LBO Spread $_{t-1}$

Drawing on the work of Achleitner and Figge (2014), the LBO-spread serves as a control variable, encapsulating the sentiment of the debt market. It is computed by subtracting the average yield of 10-year government bonds from Denmark, Sweden, and Norway from the yearly average yield of Moody's Baa yield index. This index is a fundamental component in this computation, representing bonds that, while considered investment-grade, stand only one grade above junk bond status (FRED, 2023). Furthermore, several accounting measures are included as control variables to account for the effect on dependent variables. The selection of variables is inspired by existing literature and financial knowledge. The variables are included as metrics one year prior to the transaction to capture the effect on expansion measures. Table 6.7 presents further insights into all variables.

Table 6.7: Comprehensive Summary of Study Variables, Definitions, Hypotheses and Sources

Dependent Variables				
H[3]	**Variable**	**Definition**	**Exp.**[4]	**Source**
	Sales CAGR	$\left(\frac{\text{Revenue}_{t+2}}{\text{Revenue}_{t-1}}\right)^{\frac{1}{3}} - 1$		Annual Reports
	EBITDA ME	$\left(\frac{\text{EBITDA}_{t+2}}{\text{Revenue}_{t+2}}\right) - \left(\frac{\text{EBITDA}_{t-1}}{\text{Revenue}_{t-1}}\right)$		Annual Reports
	ROIC	$\left(\frac{\text{NOPAT}_{t+2}}{\text{Invested Capital}_{t+2}}\right) - \left(\frac{\text{NOPAT}_{t-1}}{\text{Invested Capital}_{t-1}}\right)$		Annual Reports
	ROE	$\left(\frac{\text{Net Income}_{t+2}}{\text{Equity}_{t+2}}\right) - \left(\frac{\text{Net Income}_{t-1}}{\text{Equity}_{t-1}}\right)$		Annual Reports
	ROA	$\left(\frac{\text{Net Income}_{t+2}}{\text{Total Assets}_{t+2}}\right) - \left(\frac{\text{Net Income}_{t-1}}{\text{Total Assets}_{t-1}}\right)$		Annual Reports
	Revenue/IC	$\left(\frac{\text{Revenue}_{t+2}}{\text{Invested Capital}_{t+2}}\right) - \left(\frac{\text{Revenue}_{t-1}}{\text{Invested Capital}_{t-1}}\right)$		Annual Reports
	FCF/IC	$\left(\frac{\text{FCF}_{t+2}}{\text{Invested Capital}_{t+2}}\right) - \left(\frac{\text{FCF}_{t-1}}{\text{Invested Capital}_{t-1}}\right)$		Annual Reports
	NIBD/EBITDA	$\left(\frac{\text{NIBD}_{t+2}}{\text{EBITDA}_{t+2}}\right) - \left(\frac{\text{NIBD}_{t-1}}{\text{EBITDA}_{t-1}}\right)$		Annual Reports
	NIBD/FA	$\left(\frac{\text{NIBD}_{t+2}}{\text{FA}_{t+2}}\right) - \left(\frac{\text{NIBD}_{t-1}}{\text{FA}_{t-1}}\right)$		Annual Reports
Explanatory Variables				
H1	SBO Dummy	Primary vs. Secondary Buyouts	-	Prequin, Mergermarket
H2(A)	Pressure Investing	Transactions completed after 3.5 years of the investment period	-	Prequin
H2(B)	Complementary skills	Lead partner background (financial vs. operational)	+	Fund Websites, Linkedin

Continued on next page

[4]H denotes the specific hypothesis
[4]Exp denotes the expected sign for the results related to the hypothesis

Table 6.7 – continued from previous page

Dependent Variables				
H	**Variable**	**Definition**	**Exp.**	**Source**
H2(C)	Fund Specialization	Generalist vs. Specialized Funds	+	Prequin
H2(D)	Industry Specialization	The PE firm has owned three or more companies within the same industry prior to the buyout	+	Prequin
H2(E)	CEO Replacement	The CEO is replaced within the first year following the SBO	+	Prequin
H2(F)	Fund Size	Total committed capital of the acquiring PE fund	+	Prequin
H2(G)	Lead Partner Experience	Deals with experience as lead partner prior to the SBO	+	Prequin
Control Variables				
	EBITDA Margin	$\left(\frac{\text{EBITDA}_{t-1}}{\text{Revenue}_{t-1}}\right)$		Annual Reports
	Ln(Assets)	Logarithmic function of total assets in $t-1$		Annual Reports
	LBO Spread	The yearly average spread between Moody's BAA bond yield index and the average yield of a 10-year DK, SE, and NO government bond		Capital IQ
	Capital Structure	$\left(\frac{\text{NIBD}_{t-1}}{\text{NIBD}_{t-1}+\text{Total Equity}_{t-1}}\right)$		Annual Reports
	Quick Ratio	$\left(\frac{\text{Current Assets}_{t-1}}{\text{Current Liabilities}_{t-1}}\right)$		Annual Reports
	NWC/Sales	$\left(\frac{\text{Current Assets}_{t-1}-\text{Current Liabilities}_{t-1}}{\text{Revenue}_{t-1}}\right)$		Annual Reports

6.7.2 Empirical Design

Ordinary Least Squares (OLS) regression formula, Research Question 1:

$$\text{KPI}_{AOP} = \beta_0 + \beta_1(SBO) + \beta_2(\text{Control Variable}_1) + \ldots + \beta_n(\text{Control Variable}_n) + \epsilon$$

where,

- KPI_{AOP} is the dependent variable of interest, that is, the variables selected to examine operational value

creation. The dependent variables are measured as change measures, as shown in Table 6.7.

- β_0 is the y-intercept of the regression line.
- (SBO) is the dummy variable implemented to examine differences between SBOs and PBOs.
- *Control Variable*$_1$ through *Control Variable*$_n$ represent the various control variables in the model.
- $\beta_1, \ldots, \beta_n$ are the coefficients for each of the independent variables. They represent the expected change in the KPI$_{AOP}$ for a one-unit change in the corresponding independent variable, while holding all other variables constant.
- ϵ is the error term in the model, representing the difference between the actual and predicted values of the KPI$_{AOP}$.

Ordinary Least Squares (OLS) regression formula, Research Question 2:

$$\text{KPI}_{AOP} = \beta_0 + \beta_1(Driver) + \beta_2(\text{Control Variable}_1) + \ldots + \beta_n(\text{Control Variable}_n) + \epsilon$$

where,

- (Driver) is a dummy variable that represents the driver for value creation in focus, as posited by the formulated hypothesis.
- All other parameters in the model are the same as the regression formula for Research Question 1.

Fitting Models

The model fitting process has been carried out using the Akaike Information Criterion (AIC). This metric is employed to contrast and evaluate different variations of control variables to include in the OLS regression models. It provides a balance between the quality of the model's fit to the data and the complexity of the model itself, characterized by the number of parameters within the model (Forster & Sober, 2011). The main concept behind AIC is to penalize the complexity of the model to avoid over-fitting. In this thesis, an algorithm in Python was developed to iterative determine the optimal composition of control variables using the AIC score as a benchmark. The algorithm's code snippets are provided for reference in appendix C.

The methodology applied ensures the optimal selection of control variables for the models. A comprehensive outline of the model fitting process resides in Appendix A and B, and the specific procedure for ROIC is presented in Table 6.8 below. The numerals at the top of the table represent each step in the model fitting process. Green check marks indicate control variables incorporated into the model, black crosses denote removed variables, and gray dots signify variables not included in the model. These fitting models, while providing a simplified representation of the underlying algorithm designed to minimize each model's AIC score, also deliver a detailed summary of the selection process.

Table 6.8: Model Fitting Process and Control Variable Inclusion for AIC-Score Minimization

Variables	Step 1	Step 2	Step 3	Step 4	Step 5	Model fit
EBITDA Margin	✓	✗	✓	✗	✓	
Ln(Assets)	•	•	•	•	•	
LBO Spread	•	•	•	•	•	
Capital Structure	•	✓	✓	✓	✓	
Quick Ratio	•	•	•	✓	✓	
NWC/Sales	•	•	•	•	•	
AIC Score	686.7	428.5	426.3	411.9	401.3	401.3

✓ denotes that a control variable is added to the model
• signifies that the corresponding control variable is not included in the model
✗ denotes that the control variable is excluded from the model

6.8 Statistical Properties and Assumptions

In the analysis, it is critical to be observant and focused on the statistical properties of the sample observations. The three main statistical properties that will be addressed when working with the data are: I) outliers and generally the first four moments[5] in the sample, II) heteroskedastic standard errors, III) assurance of the central limit theorem (CLT) in the sample data.

Outliers and Higher Moments

The central tendency of the distribution may imply a normal distribution, yet a more detailed examination of higher moments likely uncovers significant outliers. Skewness and kurtosis measures, capturing the asymmetry and 'tailedness' of distribution, often highlight the presence of such extreme outliers (Linton, 2019). These deviations may emerge from diverse scenarios, from a portfolio company declaring bankruptcy to achieving groundbreaking innovation. Such events introduce deviations from the mean, thereby influencing the overall shape of the distribution. Furthermore, given that certain ratios incorporate components from the balance sheet, presenting a snapshot of the company's financial position at a specific point in time can magnify the variance, skewness, and kurtosis in the samples.

Heteroskedastic Standard Errors

This issue of heteroskedasticity adds a layer of complexity to the analysis. To mitigate this concern, the analysis will implement robust standard errors using the StatsModels module in Python. Heteroskedastic robust standard errors provide a practical solution by correcting the standard errors in the presence of heteroskedasticity, thus ensuring more reliable estimates (Linton, 2019). With robust standard errors, the variance of the error term can be irregular across observations without compromising the validity of the estimates. It effectively adjusts the standard errors to be unbiased and consistent, enhancing the robustness of the analysis. Consequently, applying robust standard errors ensures the validity of the estimation process despite the anticipated heteroskedasticity stemming from the financial data in the sample.

[5]The first four moments are: I) Mean II) Variance III) Skewness IV) Kurtosis

Central Limit Theorem and Assumption of Normality

While the Central Limit Theorem indicates that the sample mean's distribution will approximate normality given a sufficiently large sample size, this assumption may not hold in the context of financial data, specifically PE buyouts. Despite having a sample size, $n > 30$, deemed satisfactory by conventional standards, it might not adequately harness the power of the Central Limit Theorem, particularly compared to other disciplines (Linton, 2019). Furthermore, the inherent nature of balance sheet data, recording a specific temporal snapshot instead of a smooth transition, can amplify the likelihood of significant outliers, thereby challenging the assumption of normal distribution.

In summary, the ensuing statistical analysis will contend with outliers, heteroskedasticity, and potential deviations from normality. These characteristics underscore the necessity for a judicious approach to data analysis and emphasize the importance of implementing robust techniques to manage these complexities.

Ordinary Least Squares (OLS) Estimation

In the endeavor for an in-depth analysis of the dataset, this study utilizes the OLS regression model for its robustness and accuracy in estimations. The OLS model is a commonly used technique for regression analysis in econometrics, as noted in the literature review in chapter 4. The OLS regression model has been chosen due to its capability to deliver the Best Linear Unbiased Estimator (BLUE) of the parameters, assuming the Gauss-Markov conditions are fulfilled. These conditions pave the way for the efficiency of OLS among linear unbiased estimators (Westfall & Arias, 2020).

The Gauss-Markov theorem lists five conditions, which are assessed briefly for the model and data:

1. **Linearity in Parameters:** This condition requires the relationship between the independent and dependent variables to be a linear function of the parameters (Westfall & Arias, 2020). Variables have been selected that theoretically and logically exhibit a linear relationship, as supported by the exploratory analysis of the data. Additionally dummy variables fulfills the linearity requirement by default, strengthening the linearity assumption.

2. **No Perfect Multicollinearity:** The model's independent variables are not perfectly correlated (Westfall & Arias, 2020). Given the unrelatedness of the variables, the assumption of multicollinearity seems reasonable, thereby enhancing the reliability of individual coefficient estimations.

3. **Zero Conditional Mean:** The expected error term, given the independent variables, is zero, ensuring unbiased estimates (Westfall & Arias, 2020). Care has been taken to include pertinent variables in the model to minimize omitted variable bias.

4. **Homoscedasticity:** The variance of error terms is constant across all independent variable levels. The presence of heteroskedastic standard errors are being addressed by employing heteroskedastic robust standard errors.

5. **No Autocorrelation:** The error terms do not correlate with each other. Despite the low likelihood of autocorrelation in the standard errors, this aspect will be assessed via the regression outputs and addressed accordingly.

By adhering to these conditions, the OLS regression model's output can be relied upon for valid inferences. The model's efficiency enables confident interpretation of the relationships among variables. Moreover, its unbiasedness ensures that the model parameters are neither overestimated nor underestimated on average. The robustness of the OLS model, even under some assumption violations, depends on the nature and extent of the violation (Westfall & Arias, 2020). To conclude, the OLS model is suitable for the data and fulfills the

analytical requirements of this study. Its simplicity, computational ease, and interpretability further support its selection for this research.

7.0 Descriptive Statistics

This chapter outlines the data sample's composition within the treatment group and illustrates the characteristics of both the SBO and PBO samples. Emphasis is placed on the distribution of observations across years, countries, and industries, aiming to elucidate the data's behavioral patterns and distribution. Data pertinent to each hypothesis is then systematically exhibited, noting that the observations vary across distinct hypotheses. This portion concludes with an in-depth overview of the key descriptors for the dependent variables linked to SBOs and PBOs. The objective of this chapter is to equip the reader with a detailed understanding of the dataset used to address the research question.

7.1 Data Composition of the Treatment Groups

The treatment group data set encompasses a total of 250 observations. It reveals a distribution of 103 SBOs and 147 PBOs. The SBO sample includes 54 observations in Sweden, 25 in Denmark, and 24 in Norway, indicating a higher transaction frequency in Sweden. Intriguingly, the application of the extraction method on 2200 PBOs produced 147 observations, exhibiting a distribution pattern akin to the SBO sample, as depicted in figure 7.1. The PBO sample incorporates 74 observations in Sweden, 32 in Denmark, and 41 in Norway.

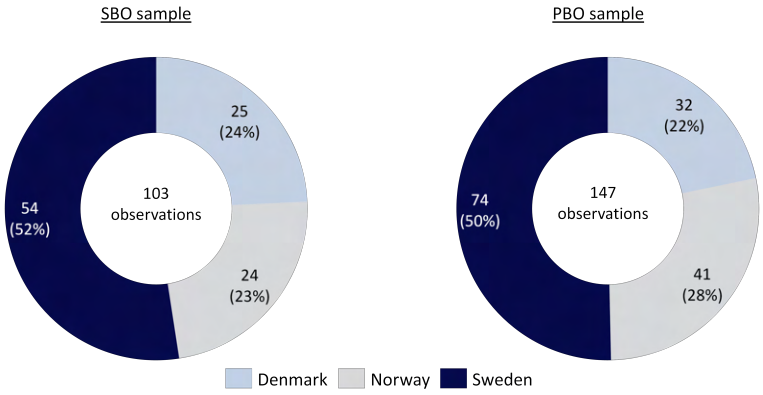


Figure 7.1: Comparison of SBOs & PBOs Distributions Across Scandinavian Countries

Further examination of the treatment group dataset reveals an apparent skewness in the data distribution towards the latter part of the time series. Notably, a significant proportion of the transactions within the samples occurred during 2010-2019. Figure 7.2 depicts the distribution of buyout types across the time series. The 2010 to 2019 period appears to echo the increased prevalence of PE investments in the Nordic region. Additionally, the progression of buyout activity parallels the economic expansion that ensued after the financial crisis. Such recession sensitivity is demonstrably observable within the SBO and PBO samples. Even though

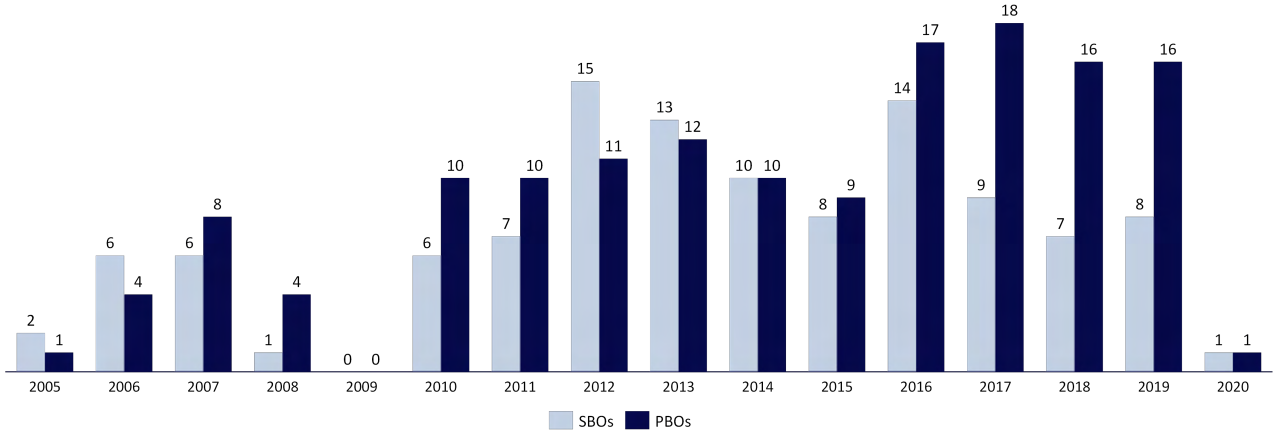


Figure 7.2: Comparative Distribution of PBOs & SBOs in the Sample

2020 experienced a brief recession due to the coronavirus pandemic, the shortest in recorded history, its impact is nonetheless noticeable within the thesis's sample.

Further examination of the transaction distribution across FF10 industry classifications reveals an over-representation of certain industries within the treatment group samples. figure 7.3 illustrates the distribution of FF10 industries. The figures above the chart indicate the total number of observations in the respective comparison group.

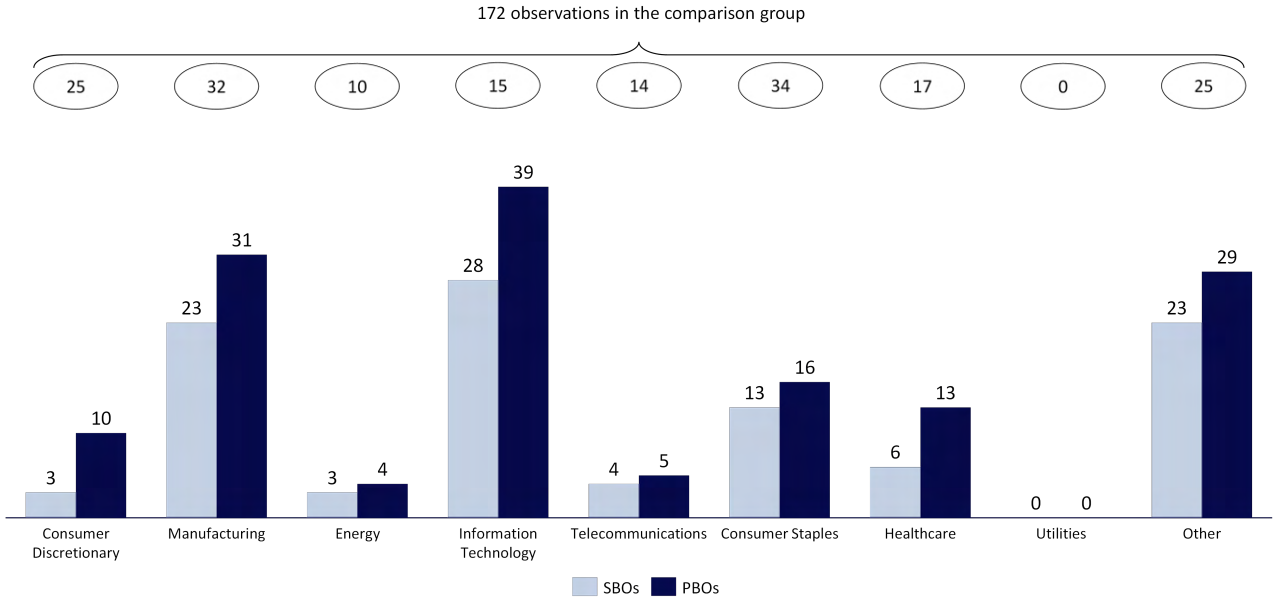


Figure 7.3: Industry Distribution for Treatment- & Comparison Groups

The Information Technology sector, along with industries such as Manufacturing, is markedly over-represented in both samples. Such over-representation suggests a possible preference among PE funds for these sectors within the Nordics. The disproportionate representation of specific sectors could skew aggregate-level results. For example, if the Information Technology sector demonstrates superior operational performance, its over-representation could exaggerate the overall performance of SBOs or PBOs. Nonetheless, such bias should be sufficiently mitigated through the industry matching approach employed with the comparison group, thereby

neutralizing general market effects. Furthermore, the relative distribution of transactions across industries between SBOs and PBOs reinforces the sample's comparability. The screening process for industry peers resulted in 172 observations. Initially, the intent was to align the comparison group size with the respective FF10 industry. However, restrictions on financial data availability limited the company count in the control groups. Even so, the comparison group observations maintain proportionality with their corresponding industries.

7.1.1 Explanatory Variables Related to Research Question 2

The second research question identifies and tests potential drivers of operational value creation in SBOs. Hence, the PBO sample is obsolete in relation to the research question 2. The following subsections will delve into the explanatory variables and assess the underlying data.

Pressure Investing

Pressure investing is identified as a key factor influencing PE funds to engage in SBOs (Arcot et al., 2013; Wang, 2012). Central to the discussion is the inquiry of whether GPs utilize SBOs as a money-burning device to garner management fees, with the effect of this approach potentially manifesting in operational performance measures. Existing literature further indicates a direct correlation between pressure investing and diminished returns. The sample for SBO analysis consists of 102 observations, with the distribution outlined in the figure 7.4.

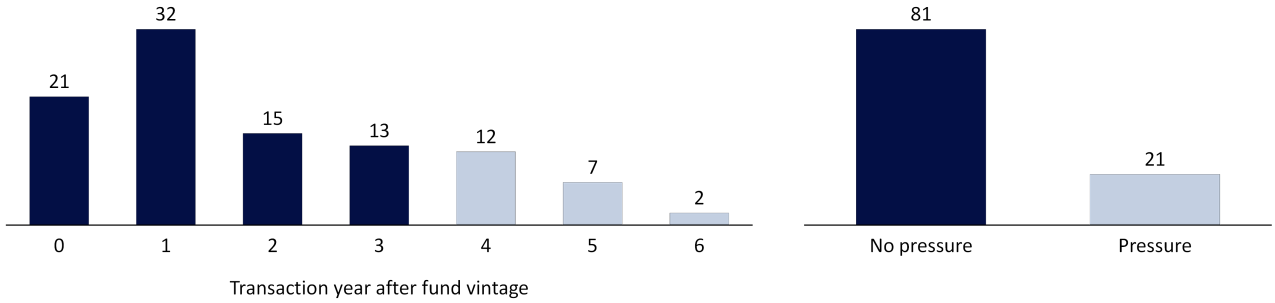


Figure 7.4: Lifecycle Buyout Distribution

Figure 7.4 indicates that the bulk of SBOs in Scandinavia occur within the first two years following the fund vintage. Consequently, the distribution of observations in the regression model leans toward deals with no pressure. Some research provides statistically significant evidence suggesting that pressure SBOs underperform compared to other buyouts (Wang, 2012). Therefore, examining the impact of pressure investing on Nordic SBOs warrants consideration. Additionally the subsequent chart elucidates the distribution of fund vintage years within the SBO sample.

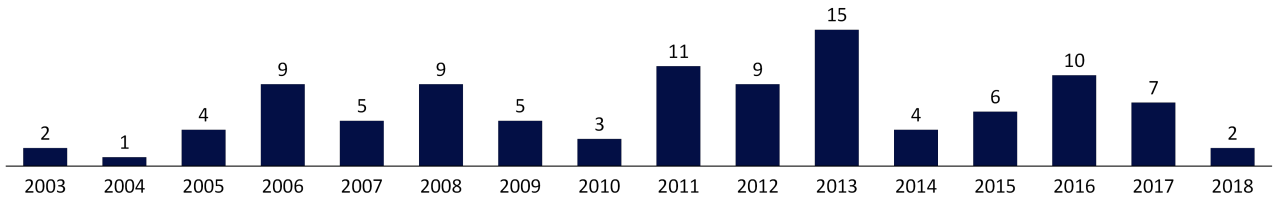


Figure 7.5: Distribution of Fund Vintages

Complementary Skills

Complementary skills at the lead partner level significantly improve deal performance and operational outcomes (Acharya et al., 2011; Degeorge et al., 2015). However, due to data availability, the sample comprises only 54 observations, in relation to examining this hypothesis. The distribution of these observations is depicted in figure 7.6.

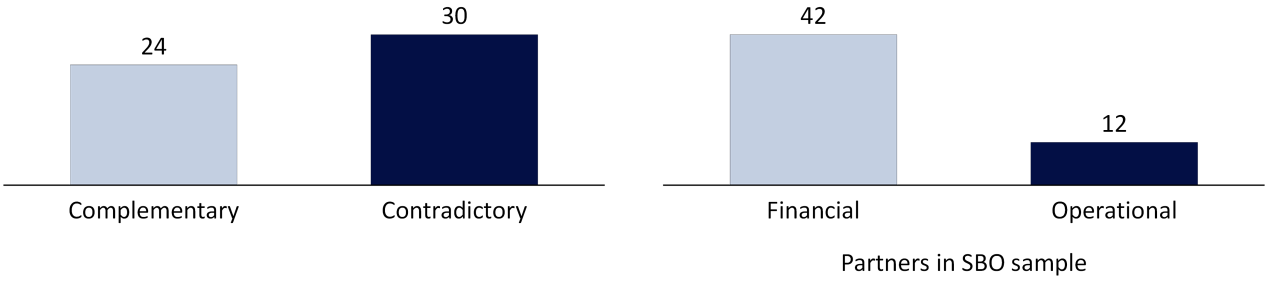


Figure 7.6: Complementary Skills in SBO Sample

Left side shows that transactions involving lead partners with complementary skill sets constitute a considerable proportion of the 54 observations. The right side reveals that lead partners with financial backgrounds predominantly feature in the SBO sample. This dominance implies that the dummy variables may exhibit bias toward financial partners. The PBO sample displayed slightly greater presence of lead partners with operational backgrounds (18 operational and 36 financial).

Specialization

The subject of specialization splits into two distinct hypotheses, focusing on fund specialization and industry specialization. Current literature offers mixed results regarding operational performance (Bruining et al., 2011; Grüner & Marburger, 2022). The sample comprises 102 observations, with their distribution depicted in the figure below.

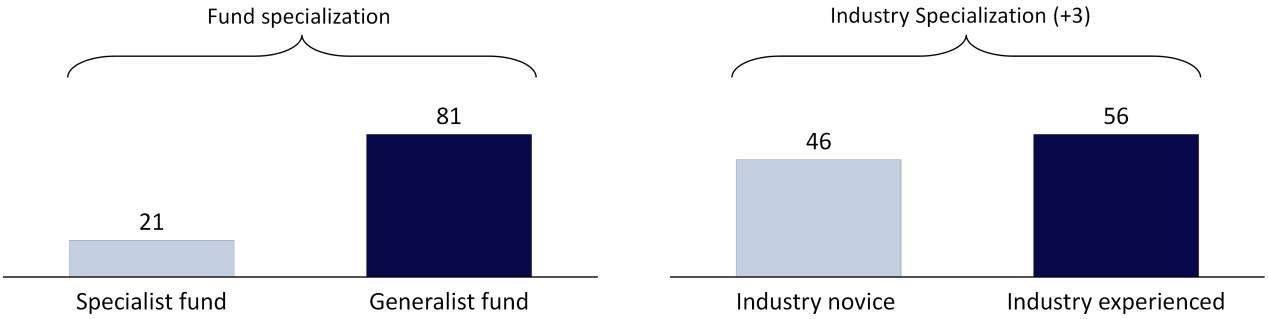


Figure 7.7: Fund & Industry Specialization in SBO Sample

The left-hand side reveals the predominance of generalist funds within the SBO sample, making up 80% of the observations. Given the interest in this hypothesis, an alternative hypothesis was developed around industry specialization, demonstrating a more evenly distributed set of observations. Nonetheless, the arbitrary measure of +3 industry companies may not be a suitable gauge of specialization.

CEO Replacement

CEO replacement is recognized as an integral component of the VCPs highlighted in figure 3.3 in the PE toolbox. The incidence of CEO replacement within the first year of ownership in the SBO sample approximates a third

(31%). This ratio closely aligns with the frequencies reported in the reviewed literature in chapter 4, where 37% and 16% of CEOs were (Guo et al., 2009; S. Kaplan, 1989). The sample encompasses 102 SBO transactions, with 32 observations indicating CEO replacement, as illustrated in the subsequent chart.

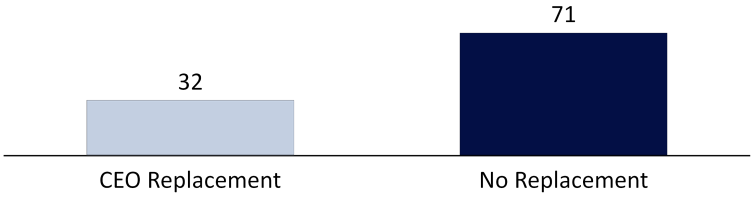


Figure 7.8: Frequency of CEO Changes Within the First Year of Ownership in SBO Sample

In Chapter 2, management experience and competencies were identified as key characteristics of the strong buyout candidate. Moreover, S. Kaplan (1989) argues that the management teams possess critical knowledge about the business. In light of this, it is intriguing to explore whether a new CEO correlates with improved operational performance.

Fund Size

In this analysis, fund size, defined as the aggregate of committed capital raised by the acquiring PE fund, serves as a crucial metric. While predominant literature measures firm size by evaluating the AuM during the transaction year (Foldager & Mølbak, 2020; Harris et al., 2014; Humphery-Jenner, 2012; S. N. Kaplan & Schoar, 2005; Skibsted & Thelin, 2018), this study opts for an approximation approach. It factors in fund size as an obvious approximation for PE firm size as noted by Stowell (2018). The sample for the fund size hypothesis includes 103 SBO transactions. A detailed depiction of fund size and the corresponding categorical variables pertinent to the regression analysis can be found in figure 7.9.

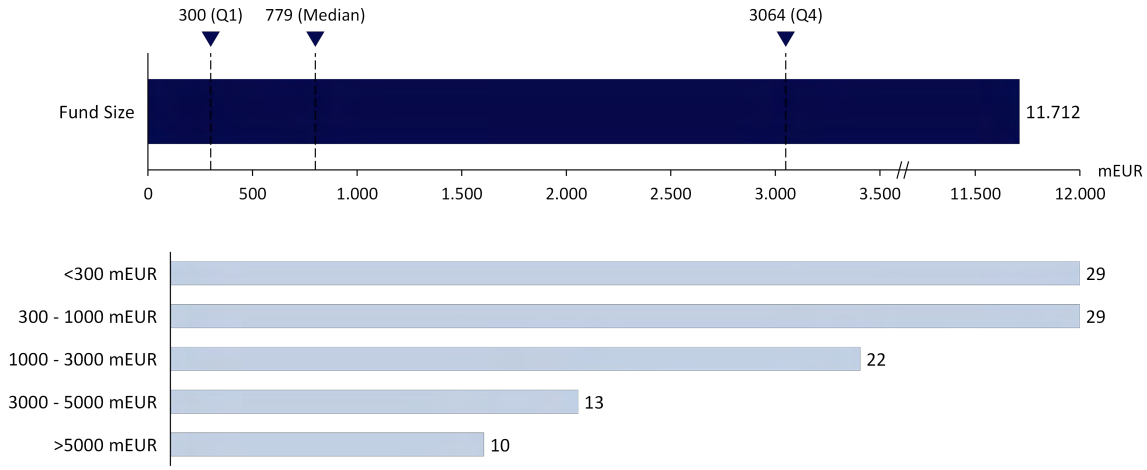


Figure 7.9: Categorization and Distribution of Fund Sizes within the SBO Sample

The fund size within the sample ranges from 67 to 11,712 mEUR, with a median value of 779 mEUR. The first and third quartiles are respectively set at 300 mEUR and 3,064 mEUR. The fund sizes have been segmented into groups, each representing a distinct range. The distribution among these groups leans towards 'smaller' funds, suggesting a higher frequency for funds ¡ 779 mEUR in Scandinavia.

Lead Partner Experience

The Lead Partner Experience, also acknowledged as the GP effect, has been defined as a determinant of returns (Loos, 2006). In the same vein, Amess and Wright (2013) establish statistically significant evidence, supporting the notion that the experience of a lead partner can have a positive influence on operational performance. The underlying study encompasses 102 distinct observations, with the distribution elucidated below, providing an insight into the dispersion of data pertinent to this hypothesis.

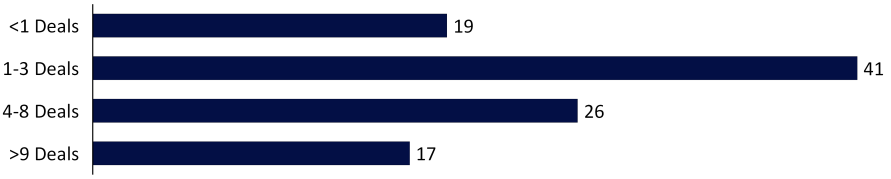


Figure 7.10: Categorization and Distribution of Lead Partner Experience Within the SBO Sample

7.2 Median & Average AOP Assessment

Before proceeding with the comprehensive analysis, groundwork is established through an initial evaluation of median AOP values for SBOs and PBOs relative to the comparison group. The subsequent table conveys these AOPs, incorporating average AOP in parentheses to give nuance and address the potential influence of outliers on extreme values.

When considering top-line growth, both buyout types outperform their public counterparts throughout the years [-1 : +2]. PBOs exhibit a marginal edge in median terms and boast a significantly superior CAGR in average terms relative to SBOs (11.3% vs. 4.9%). Consequently, SBOs demonstrate superior performance across all return and margin measures, hinting at potential spillover effects from attaining excess growth. While growth typically carries inherent costs unless secured through unique high organic growth from network effects, which is more the exception than the rule, it necessitates investments, consequently impacting margins, a trend noticeable in the samples (Koller et al., 2020).

In terms of efficiency measures, divergences are observed. The Sales/IC ratio at the median level differs markedly between SBOs and PBOs, highlighting that SBOs excel at generating revenues through invested capital compared to PBOs or at least show better proficiency at altering the ratio over the initial two years of ownership. Moreover, averages significantly deviate from median values in the PBO sample compared to a closer measure in the SBO sample. The FCF/IC ratio reveals a slight outperformance by PBOs compared to SBOs, suggesting that PBOs generate marginally superior AOP on a sample level.

In examining debt metrics, the focus turns to measures such as NIBD/EBITDA and NIBD/FA. In the former, the median ratio for SBOs is negligibly smaller compared to that of PBOs. However, when observed on an average basis, SBOs register an approximate 30% increase compared to PBOs. This suggests a higher tendency for leverage among SBOs, a trend that appears influenced by outliers within the samples. Turning attention to the NIBD/Fixed Assets ratio, the situation reverses. PBOs exhibit greater leverage against the asset base, both in terms of median and mean values within the sample. This implies a more substantial utilization of leverage by PBOs in relation to the fixed asset base.

Table 7.1: Underlying Data, Median, and Mean Values

SBO and PBO AOPs vs. Industry Matched Peers							
	SBOs			PBOs			
Dependant variables	**Obs.**	**Median**	**std. error**	**Obs.**	**Median**	**std. error**	**Difference**
Revenue CAGR	103	0.042	0.012	147	0.055	0.018	-0.013
		(0.049)			(0.113)		
EBITDA ME	103	-0.013	0.007	147	-0.027	0.008	0.014
		(-0.017)			(-0.031)		
ROIC	103	-0.085	0.030	147	-0.154	0.101	0.069
		(-0.175)			(-0.417)		
ROE	103	-0.153	0.044	147	-0.261	0.047	0.108
		(-0.195)			(-0.361)		
ROA	103	-0.057	0.010	147	-0.083	0.013	0.026
		(-0.054)			(-0.110)		
Sales/IC	103	-0.741	0.338	147	-1.337	0.988	0.596
		(-0.795)			(-3.694)		
FCF/IC	103	-0.035	0.021	147	-0.010	0.028	-0.025
		(-0.110)			(-0.064)		
NIBD/EBITDA	103	2.089	0.379	147	2.094	0.439	-0.005
		(2.385)			(2.427)		
NIBD/FA	103	0.217	0.058	147	0.511	0.376	-0.294
		(0.287)			(2.312)		

Numbers in (.) are mean values.

Sample AOP KPIs

To fully comprehend the breadth of the sample distributions, it is essential to visualize the distribution of AOPs across all KPIs. A ridgeline chart, given its ability to compare the distributions of SBOs and PBOs directly, is chosen. However, due to a measurement discrepancy, the NIBD/EBITDA measure has been omitted. These distributions, characterized by their leptokurtic nature and heavy tails suggestive of frequent outliers, are depicted in figure 7.11 below.

Interestingly, the peaks of all AOP KPI distributions fall below zero, indicating that the mode - the most frequently observed value - represents less expansion in the KPIs compared to public industry peers. For both SBOs and PBOs Sales CAGR exceeds 0% substantially in terms of both median and mean values as shown in table 7.1. The divergence is largely due to the presence of substantial outliers. For clarity, some extreme values have been deliberately omitted from the chart, meaning not all outliers are visually represented. Nonetheless, figure 7.11 provides a comprehensive representation of more than 95% of all observations, offering a detailed overview of the AOP KPIs.

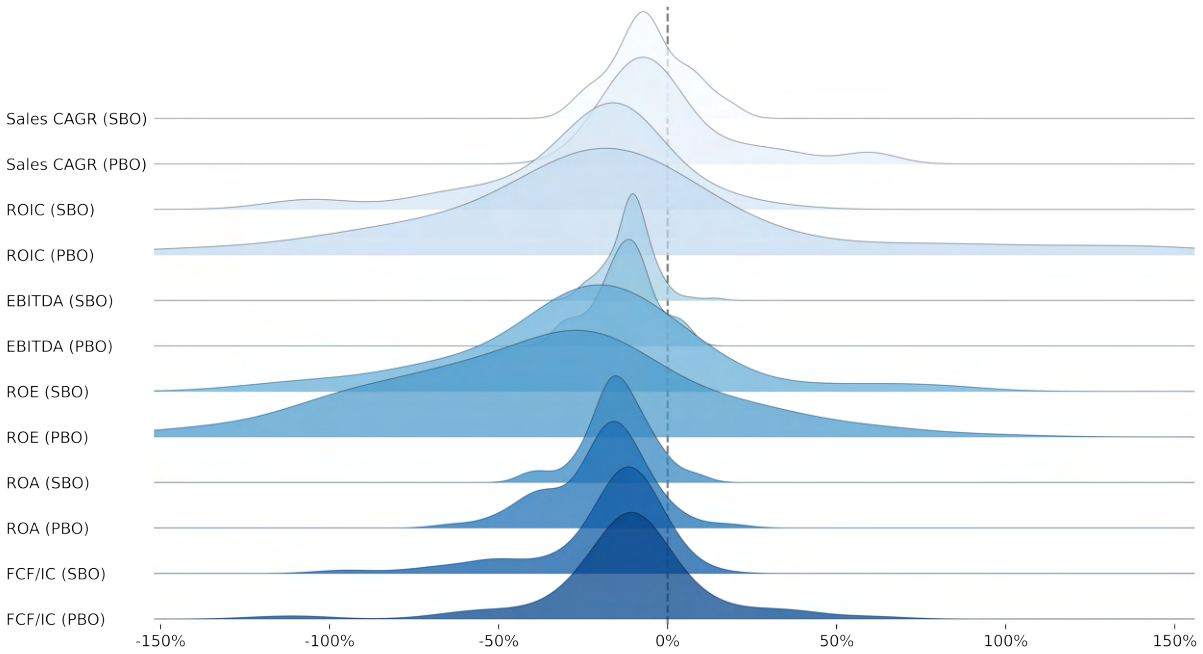


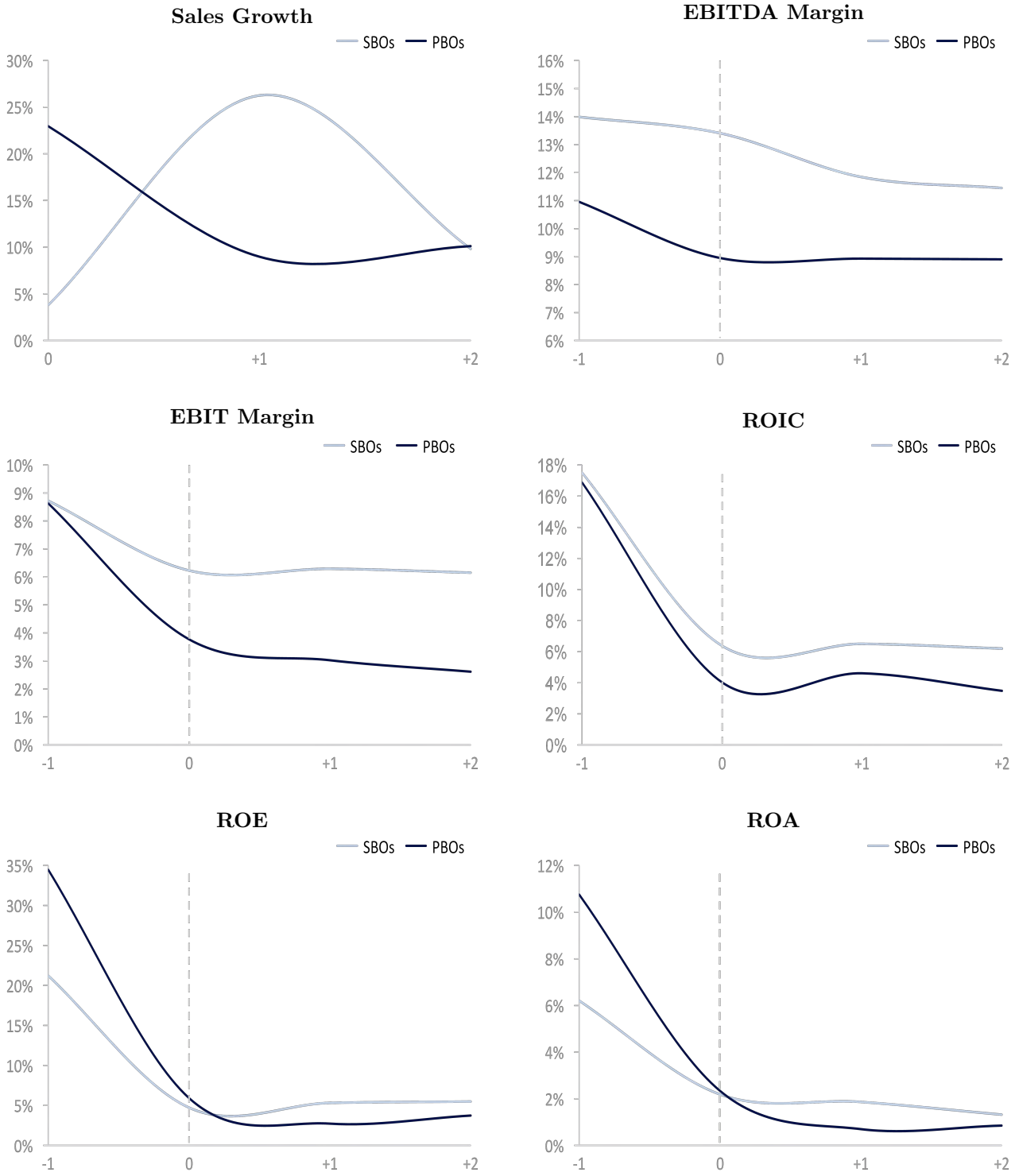
Figure 7.11: Comparative Distribution of AOP KPIs Between PBOs and SBOs

Underlying Sample Data

The subsequent pages present graphical representations of median values for both SBOs and PBOs. The primary objective of these dashboards is to offer an exhaustive view of data trends observed during the analyzed period. Additionally, these representations highlight critical financial metrics such as growth, profitability, return, efficiency, and leverage, thus providing an essential overview of performance and fluctuations over the period. The data ratios incorporated in these dashboards have been meticulously selected, with the basis for their selection rooted in the detailed analysis and interpretations that will be presented in the upcoming chapters. This careful selection of data ratios ensures that the dashboards offer valuable insights to the underlying data, AOPs are calculated on.

Dashboard (1/2)

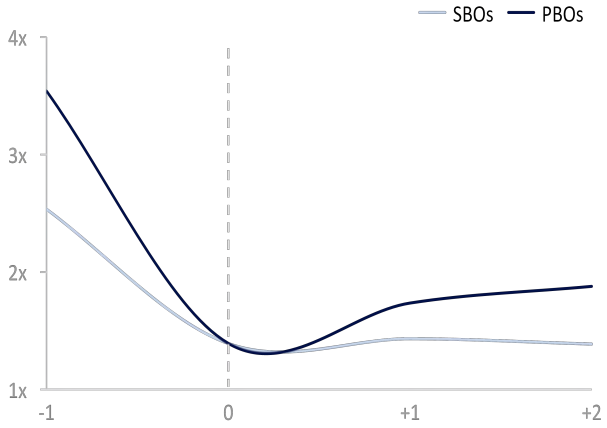
Median values from SBO and PBO datasets. The dashboard offers a comparative view of central tendencies



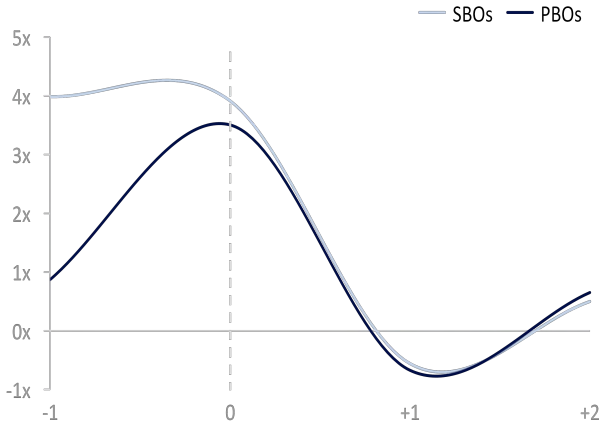
Dashboard (2/2)

Median values from SBO and PBO datasets. The dashboard offers a comparative view of central tendencies

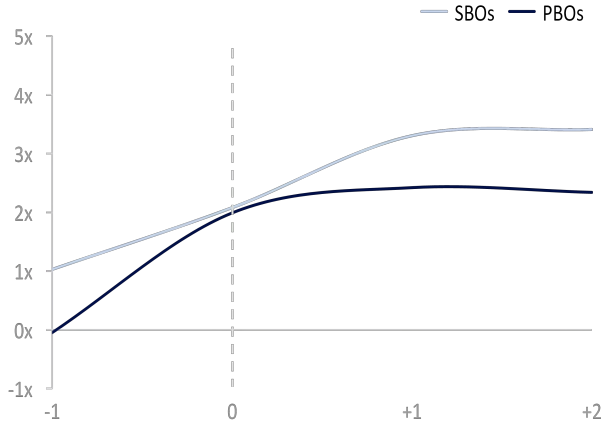
Sales/IC



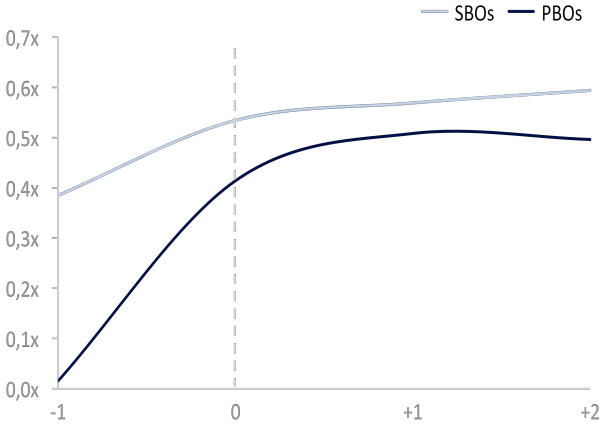
FCF/IC



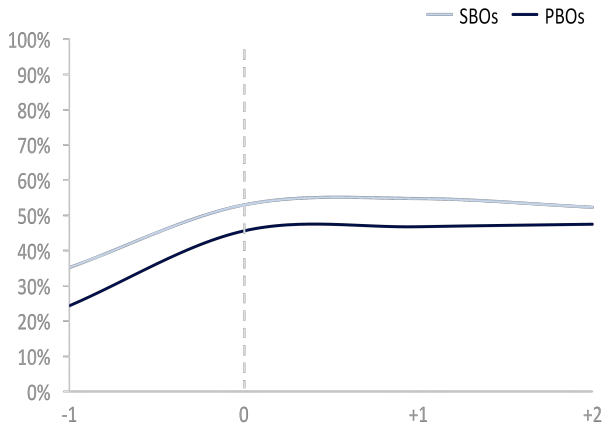
NIBD/EBITDA



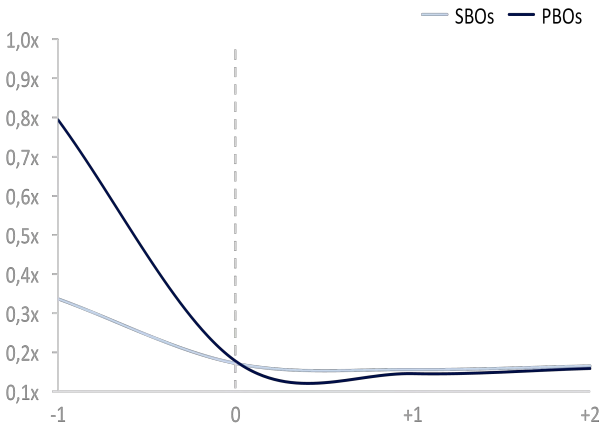
NIBD/FA



Capital Structure



EBITDA/FA



8.0 Results and Analysis

This chapter provides an econometric interpretation of the findings from the regression analysis, complemented by the extrapolation of causal effects that contribute to these results. The analysis bifurcates into two distinct parts, each corresponding to one of the research questions. The first segment delves into research question one, centered on the hypothesis of inferior operational performance in SBOs. This segment explicates the models adopted to explore differences in operational performance, further illuminating the magnitude of the findings and probable causes.
The subsequent segment is dedicated to the second research question, identifying potential catalysts or determinants that drive operational performance in SBOs. The overarching objective is to unravel the main drivers that stimulate operational value creation in SBO deals.

Empirical testing is performed in Python due to its proficiency in deploying generic models, its analytical flexibility, and efficient error rectification. The employment of scientific libraries, such as Statsmodels[1] and Scipy[2], enables the implementation of regression models tailored to address specific research queries. Results garnered from these regression models are depicted in tabular representations. For thorough inspection, detailed code snippets are made available in Appendix E. In adherence to the guidelines outlined in the methodology chapter, the data utilized for the regression models was subjected to a winsorizing process at the 5% level. The winsorization process effectively mitigates the impact of extreme outliers by truncating them, ensuring they do not disproportionately skew the results of the OLS estimations.

8.1 Evaluating Operational Performance in SBOs and PBOs

The first research question primarily concentrates on the variation in operational performance between PBOs and SBOs. The hypothesis posits that SBOs manifest sub-optimal operating value creation relative to PBOs. For a comprehensive understanding of this issue, PBOs and SBOs have been evaluated across an extensive selection of KPIs. This approach provides the depth and nuance to infer inferior operational performance in SBOs versus PBOs.

The setup of the regression model aims to discern the similarities and discrepancies between SBOs and PBOs. Taking into account the nine KPIs utilized to clarify the first research question, the focus has been on the application of an SBO dummy variable. Namely, this SBO dummy takes a value of 1 when the transaction is an SBO and 0 otherwise. A positive indicator implies that SBOs showcase superior performance on the corresponding KPI, and the opposite for a negative sign.

[1]Documentation for the library here can be found on: https://www.statsmodels.org/stable/index.html
[2]Documentation for the library here can be found on: https://docs.scipy.org/doc/scipy/

Table 8.1: Regression Output, Research Question 1

KPI	Sales Growth	EBITDA	ROIC	ROE	ROA	Sales/IC	FCF/IC	NIBD/ EBITDA	NIBD/FA
SBO Dummy	-0.038	0.010	0.013	0.046	0.025	0.338	−0.059*	0.355	−0.842***
Std. Error	0.024	0.011	0.064	0.069	0.017	0.667	0.034	0.584	0.268
Robust std. Errors	✓	✓	✓	✓	✓	✓	✓	✓	✓
P-value (t-test)	0.122	0.340	0.836	0.507	0.139	0.613	0.083	0.544	0.002
R squared	0.047	0.233	0.706	0.154	0.300	0.594	0.147	0.001	0.229
N observations	250	250	250	250	250	250	250	250	250
EBITDA-margin	✗	✗	✓	✓	✓	✓	✓	✗	✗
Ln(Assets)	✓	✓	✗	✓	✓	✗	✗	✗	✓
LBO spread	✗	✗	✗	✓	✓	✗	✗	✗	✗
Capital structure	✗	✓	✓	✗	✗	✓	✓	✗	✓
Quick ratio	✗	✗	✓	✓	✓	✓	✗	✗	✓
NWC/sales	✗	✗	✗	✗	✗	✗	✗	✗	✗

Significance at the 10%, 5% and 1% level is denoted by *, ** and *** respectively.
✓ denotes the control variable is applied in the regression for the specific KPI
✗ denotes the control variable was not applied in the regression for the specific KPI

8.1.1 Sales CAGR: An Insight into Top-Line Growth

The regression analysis underscores that SBOs display a lower CAGR in sales, by -0.038, compared to PBOs throughout the observed time series. This discrepancy coincides with fundamental statistics such as mean and median values, particularly evident when juxtaposing the AOP of SBO and PBO companies regarding their sales CAGR. Although business value is shaped by diverse factors, including growth, margins, and free cash flow, prevailing literature underscores the proclivity of PE owners to prioritize top-line growth in their VCPs. This focus on growth is reflected in the CAGR metric.

A pivotal factor contributing to the disparity in sales CAGR between PBO and SBO firms is the difference in their organizational size. The proposition that SBO companies are larger, on average, stems from the concept that they represent a subsequent ownership phase. As a result, even a minor size augmentation by the PBO owner leads to the SBO company surpassing its predecessor in terms of size. This increase in size complicates the task of achieving top-line growth, making it a more capital-intensive and challenging undertaking. This observation is congruent with previous literature that compares the sales growth dynamics between SBO and PBO firms. The superior sales CAGR exhibited by PBO companies supports the hypothesis suggesting a sub-optimal operational value creation in SBO firms.

8.1.2 Profitability

In the initial two years of ownership, the EBITDA margin in the sample of SBO firms demonstrates superior growth in AOP relative to PBO firms. The EBITDA margin for PBO firms sits at 11% in the year prior to ownership (year -1), declining to 8.9% over the subsequent two years, signaling an overall decrease. In contrast, SBO firms commence with an EBITDA margin of 15.1% in year -1, which decreases to 13.3% by the conclusion of year 2, reflecting a comparatively minor reduction in EBITDA margin throughout the initial two years. The EBITDA margin for SBOs at year -1 mirrors the higher EBITDA margin PBOs achieve at the end of the ownership period. As the subsequent method for comparison remains unutilized, this margin does not directly transpose to the PBOs in the sample. Still, it may serve as an approximation due to the substantial number of

observations statistically supporting this inference. The slightly superior EBITDA margin in SBOs throughout the analyzed period, alongside the smaller decrease, concurs with the general literature. Evidence suggests that alterations made by PE firms endure beyond the exit of the PE firm (Biesinger et al., 2020). The stability resulting from changes implemented by preceding PE owners indicates decreased volatility in the performance of a company previously owned by PE sponsors. A trade-off exists between risk and return, as stipulated by well-established economic principles: lower volatility, signifying less risk, typically results in smaller returns. In relation to the EBITDA margin, the regression analysis does not produce significant results. The p-value suggests that the difference in the transaction, whether a PBO or SBO, is statistically indistinguishable from zero. However, the congruity between the regression output and the general observations at the sample level remains noteworthy. The observation that EBITDA decreases less for SBOs at the sample level, leading to higher AOPs, contradicts existing literature. For instance, Bonini (2015) suggests that the AOP of PBOs ranges from 1.54% in the interval [-1 : 1], and SBOs range from 0.71% (Bonini, 2015). The slightly higher, although statistically insignificant, EBITDA margin in SBOs is in line with research by Achleitner and Figge (2014), who identify no significant differences in operating performance measures between SBOs and PBOs (Achleitner & Figge, 2014).

8.1.3 Return Metrics

Return on Invested Capital (ROIC)

Throughout the examined period, both SBOs and PBOs depict a decline in ROIC at the sample level. PBOs exhibit a median of 16.87% and 3.48% in the interval [-1 : +2], equating to a decrease of -13.39% over the two years of ownership. The decrease in ROIC for SBOs is less pronounced, standing at 17.5% and 6.21% within the same interval, yielding a decline of -11.29%. This shift is driven by a significant rise in invested capital early in the ownership period, followed by lower NOPAT for both SBOs and PBOs, resulting in a negative shift in ROIC.

These observations align with other analyzed metrics, indicating a challenge in expanding margins over a short horizon. There seems to be a trend where PBOs manifest more volatile fluctuations in performance measures through the first two years of ownership. The regression output provides the ROIC of SBOs with a positive coefficient, echoing observations in the raw data. Nevertheless, a high p-value does not denote significance, meaning inference about PBOs and SBOs differences in the regression setup cannot be confirmed. Despite the non-significance, understanding the dynamics driving the observed disparities remains valuable. The R-squared of 70.6% indicates correct specification, as 70.6% of the variance is explained by the variables in the model. The change in ROIC has a principled basis, given the growth analyzed earlier, with both PBOs and SBOs achieving top-line growth from the first year of ownership. There's a natural trade-off between growth and margins, with growth requiring increased capital intensity, potentially suppressing margins in the short-term but fostering long-term value creation (Koller et al., 2020). ROIC is not particularly in the scope of the reviewed literature. However, the authors believe it is a key metric that should be analyzed when assessing operational value creation.

Return on Assets & Equity

Both ROE and ROA show similar patterns within the period analyzed. Quite surprisingly, both ROA and ROE metrics have a higher starting point in the year preceding the PBO acquisition (year -1), that is, prior to the involvement of a financial sponsor. The drivers behind the negative shifts over the time frame examined can be

predominantly attributed to considerable increases in equity between [-1 : 0], for instance, a surge of 75% for SBOs and a significant 116% for PBOs in median terms. Concurrently, net income registers a decrease of -61% for SBOs and -69% for PBOs in the same interval. This negative correlation between net income and equity contributes to the downward trajectory in the ROE measure. An intriguing pattern was identified during the data collection process: depreciation escalated as PE ownership entered, subsequently reducing EBIT. Alongside this, high debt levels often led to substantial interest expenses, frequently compressing net income close to zero or even into negative territory. In the year before the PBO, 21 of the 147 sample companies registered negative net income. However, in the year of the PBO, the number of companies with negative net income increased to 62, approximately three times the initial number. For the SBO sample comprising 103 observations, 15 companies registered negative net income in year -1, which increased to 41 companies in the year of the buyout. ROA mirrors the same trend as observed in ROE. The more significant volatility in the evolution of ROE and ROA is particularly evident in PBOs. However, the regression model does not provide a robust representation of these ratios, with ROA's R-squared value of 30% and ROE's at 15.4%. Although there is almost slight significance in ROA's p-value at the 10% level, caution is advised when drawing inferences close to or below the 10% level of significance from an econometric standpoint. In contrast, the regression output does not suggest a discernible difference in ROE whether the transaction involves an SBO or a PBO. On the other hand, the p-value for ROA does not quite reach significance at the 10% level.

8.1.4 Efficiency

Sales to Invested Capital

The Sales/IC ratio serves as an additional metric for evaluating a company's efficiency in value creation, with a high ratio indicating effective capital rotation and sales generation (Mauboussin & Callahan, 2022).

For the samples analyzed, it is essential to recognize that mechanical factors primarily impacting the ratio's denominator significantly influence this ratio's expansion time horizon. This may lead to potential misconceptions. For example, in PBOs, the company operates as a standard entity before the buyout, maintaining a lower invested capital than a recently acquired portfolio company.

PE ownership is characterized by substantial leverage, with a significant increase in leverage and equity inflating the invested capital once a PE owner enters. This inflation impacts the denominator of the Sales/IC ratio, potentially affecting the likelihood of achieving a high ratio and indicating a notable change in financial performance. During the PE ownership period, decreased debt and leverage led to a diminished invested capital base and a consequent increase in the Sales/IC ratio. With SBOs, this ratio is initially high, but as the secondary PE owner re-leverages the company, the invested capital base grows, decreasing the ratio short-term. Contrary to the initial hypothesis suggesting PBOs would exhibit greater expansion in efficiency ratios over the analyzed period, the sample reveals considerable activity in financial ratios and measures around the time of the buyout. This activity primarily involves changes in invested capital and significant volatility in profitability measures.

For SBOs, the average invested capital increases from 56 mEUR to 125m EUR from the year preceding the buyout to the buyout year. This substantial increase explains the negative sign of both SBO and PBO AOPs compared to publicly traded peers. Over the same horizon, the invested capital of SBOs increases by 124% (average values) and 154% (median values). For PBOs, the average and median increases are 155% and 321%, respectively. This trend supports the observed negative sign in AOPs and the positive coefficient on the SBO dummy, indicating the challenge of expanding Sales/IC over just two full years of ownership with such growth rates in the denominator. Furthermore, the R-squared value of 61.3% suggests that the model is reasonably

successful in explaining the variance. However, with a p-value of 0.594, the null hypothesis that the coefficient is not zero cannot be rejected, implying the inaccuracy of making inferences about the differences in coefficients based on whether the transaction was an SBO or PBO.

FCF to Invested Capital

Analyzing a firm's capacity to generate free cash flow (FCF) from invested capital is intriguing, given FCF's central role in most valuation models and its importance in evaluating a firm's capital efficiency. The regression model demonstrates modest significance at the 10% threshold concerning SBOs. However, a negative coefficient suggests a slight negative impact on the FCF/IC ratio for SBOs compared to PBOs. An R-Squared value of 14.7% indicates a low degree of model fit. A review of the raw data is necessary for deeper preliminary analysis. SBOs show a decrease in FCF from [-1 : +2], starting at 4% and decreasing to 0.5%, a reduction of -3.5% in absolute terms. In contrast, PBOs display negligible alteration (0.9% to 0.7%), explaining the negative coefficient in the regression outcome. Invested capital increases by 168% for SBOs and 356% for PBOs over the analyzed period, impacting the FCF/IC ratio. While PBOs exhibit a median decline of -22% in FCF, average figures suggest a substantial increase in FCF (growing by a factor of 8.11), indicating high-performing outliers. SBOs display a decline of -47.5% but an average increase of 48.3%, indicating the presence of significant performers, albeit fewer than PBOs. The remarkable FCF expansion within the initial two ownership years for PBOs is noteworthy, suggesting the occasional ability to generate significantly more cash flow. The principal difference between PBOs and SBOs is that SBO transactions are typically larger in size, asset base, and price. FCF arises from alterations in operational items or working capital, investments, and financial items. These components represent the primary factors influencing cash flow generation, leading to a significant correlation between FCF and invested capital. Borrowing can augment cash flow, while debt repayments reduce FCF. Effects of equity are often less observable. An increase in equity resulting from share issuance or retained earnings will enhance FCF, the latter via the operating section of the cash flow statement. The substantial growth in invested capital for the period of [-1 : 2] contributes to the negative coefficient in the SBO dummy. This increase is accompanied by a relatively minor reduction in FCF over the same timeframe for PBOs relative to SBOs. The observed disparities yield the significance elucidated by the regression output. SBOs' propensity to accrue high levels of debt may increase associated interest expenses, thereby diminishing FCF. Conversely, PBOs typically do not raise leverage to the same extent, enabling more efficient FCF generation. This hypothesis, based on the available data, may explain the observed FCF variations in different buyouts. Further dissection of the cash flow statement would be required to gain additional insights. However, such analysis lies beyond the scope of this thesis.

8.1.5 Debt Measures

Debt, or leverage, represents a significant dimension of PE. To shed light on this value generation component, distinctions in NIBD/EBITDA and NIBD/FA were evaluated. Credit institutions often utilize the NIBD/EBITDA ratio as a cash flow-based debt measure. Notably, lenders may establish covenants based on this debt to EBITDA multiple (Stowell, 2018). Regression analysis illuminates elevated NIBD/EBITDA for SBOs. Despite the model's R-Squared value lying below 1%, indicating a limited explanation of the variance, the OLS output echoes findings from previous research. Scrutinizing median data for SBOs unveils a NIBD/EBITDA ratio of 0.77 in the year prior to the buyout, escalating to 2.1 two years after the buyout. The mean NIBD/EBITDA ratio exhibits a similar increase from 1.74 to 4.99. This rising trend is not as prominent for PBOs, where the median NIBD/EBITDA ratio grows from 0.12 to 1.8 and the mean from 0.71 to 1.87. A marked disparity emerges between the two buyout types due to the SBO sample containing cases with larger increases. Regarding

the leveraging of the fixed asset base, the PBO sample surpasses SBOs. The R-Squared value of 22.9% indicates a model specification that may not be the optimal choice for explaining the variation in data. Nevertheless, the p-value for the SBO dummy at the 1% significance level implies a high confidence that the coefficient is not zero, which justifies a definitive inference about the coefficient. The NIBD/FA ratio also distinguishes differences between SBOs and PBOs. For PBOs, the median increase over the analyzed period stands at 48%, compared to 21% for SBOs, with the average change being 232% for PBOs and 29% for SBOs. This disparity underscores a considerable variance between the two samples. Exploration of the capital structure shows that SBOs' median debt level increases from 27% in the year prior to the buyout to 47% in the year of the buyout. In comparison, PBOs see their debt level rise from 12% to 39% over the same period. Across all years, SBOs consistently maintain higher debt levels in their capital structure, a trend also evident in the NIBD/EBITDA measure. However, this trend is less obvious when examining the NIBD/FA measure. A plausible explanation considers the larger size of SBOs and the substantial capital strength of PE funds. For PBOs, this capital strength is more critical due to their smaller asset base, which allows them to generate more leverage relative to their assets. The lower nominal capital required for the GP to leverage the fixed assets enables PE funds managing PBOs to generate significant leverage. Conversely, the nominal debt required to leverage the fixed assets in SBO-owned companies is notably larger. Although this analysis will not delve further into the impact of separating buy-and-build strategies on the NIBD/FA ratio, it is essential to note that goodwill can significantly influence fixed assets. Buy-and-build strategies have the potential to distort the fixed asset base due to an excess amount of goodwill on the asset side, impacting the denominator in the ratio. The excess NIBD/EBITDA is good rooted in existing literature, where general findings show that SBOs obtain more debt compared to PBOs; for instance Achleitner and Figge (2014) finds that SBOs obtain 28-30% more leverage in terms of NIBD/EBITDA (Achleitner & Figge, 2014).

8.2 Results and Analysis: Research Question 2

8.2.1 Pressure Investing

The results on pressure investing is based on hypothesis H2(A), which is inspired by existing literature (Arcot et al., 2013; Wang, 2012).

H2(A): *"Pressurized investments exhibit inferior operational performance relative to other SBOs"*

PE funds possessing a substantial amount of uninvested capital towards the investment period's conclusion tend to favor SBOs and typically invest at elevated valuations (Arcot et al., 2013). A deep-dive into operational performance reveals that SBOs succumbing to pressure investing display lower operational performance than their counterparts, with sales growth estimated to be 32.4% lower (Wang, 2012). Consequently, it is anticipated that SBOs exhibit inferior operational performance when subjected to pressure investing.

The outcomes derived from the regression model are exhibited in table 8.2.

Table 8.2: Regression Output Research Question 2, Pressure Investing

KPI	Sales Growth	EBITDA	ROIC	ROE	ROA	Sales/IC	FCF/IC	NIBD/ EBITDA	NIBD/FA
Pressure Investing	0.008	-0.006	0.155***	0.184**	-0.001	0.825	0.056	-0.424	0.079
Std. Error	0.024	0.013	0.050	0.085	0.018	0.696	0.042	0.774	0.110
Robust std. Errors	✓	✓	✓	✓	✓	✓	✓	✓	✓
P-value	0.732	0.645	0.003	0.032	0.964	0.239	0.185	0.585	0.476
R squared	0.008	0.126	0.337	0.191	0.262	0.102	0.231	0.061	0.340
N observations	102	102	102	102	102	102	102	102	102
EBITDA-margin	✗	✓	✗	✓	✗	✗	✓	✗	✗
Ln(Assets)	✗	✓	✓	✓	✓	✗	✗	✓	✗
LBO spread	✗	✗	✗	✗	✗	✗	✓	✓	✗
Capital structure	✗	✗	✓	✗	✓	✓	✓	✓	✓
Quick ratio	✗	✗	✗	✓	✗	✗	✓	✗	✗
NWC/sales	✓	✗	✗	✗	✗	✗	✗	✗	✗

An interpretation of these results engenders uncertainty about whether pressure investing influences operational performance, as only ROIC and ROE demonstrate statistical significance. SBOs succumbing to pressure investing present positive coefficients of 0.155 and 0.184 on these KPIs. On the contrary, the R-squared values, indicative of the variance proportion in the dependent variable that can be predicted from the explanatory variable, remain consistently low. The heightened coefficient on ROE could be accounted for by the negative coefficient of NIBD/EBITDA. This suggests lower leverage levels, thereby reducing invested capital, which is factored in while computing ROIC (Plenborg & Kinserdal, 2021). As a consequence, the equity multiplier experiences an increase, possibly elevating ROE.

Efficiency measures yield unexpected coefficients. The coefficient of 0.825 indicates that pressure SBOs register an expansion in Sales/IC relative to their counterparts. Simultaneously, these SBOs seem to generate a superior FCF/IC ratio by 5.6%. Considering these results lack statistical support, the null hypothesis stating that the coefficient is statistically distinct from zero cannot be rejected. Various factors could account for the outcomes regarding H2(A). One plausible explanation for the higher return measures could be that funds under pressure opt for more selective targets, choosing firms that offer the most promising returns (Stowell, 2018). This could clarify the positive return coefficients, particularly in the short run, owing to the measurement window. In line

with findings from research question one, buyouts often encounter negative net income post-transaction year. If the supposition that pressure investing corresponds to the selection of stable performers holds true, then the discrepancy between negative and positive net income could elucidate the positive coefficient for ROIC and ROE, as evidenced by statistical significance.
Selection might emphasize cost reduction, efficiency enhancements, or other operational modifications. The coefficient on EBITDA seems to narrate a different story. A deeper look into the data reveals that the median EBITDA margin contracts at 3.2% for pressure SBOs and 1.6% for other SBOs throughout the scrutinized period. It is imperative to remember that these median values are not benchmarked against the comparison group to account for time and industry effects. Another plausible explanation for the results could be the temporal distribution of observations. To probe this issue further, the distribution of observations between the explanatory dummy variables is illustrated in figure 8.1.

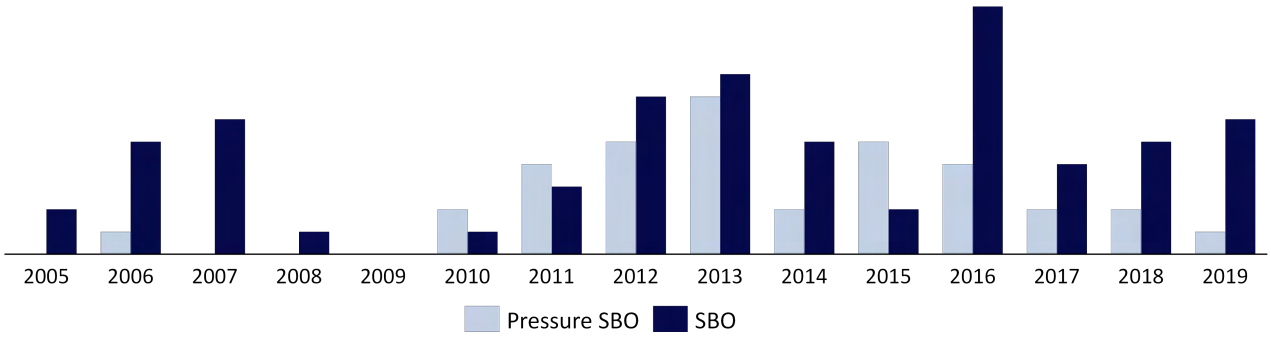


Figure 8.1: Comparison of SBOs & PBOs Distributions Across Scandinavian Countries

The sample shows a skewed tendency across transaction years that could affect the model output. It is evident that a significant number of pressure SBOs occur during a period characterized by favorable debt market sentiment and equity market conditions. Even after adjusting for time and industry effects, this distribution poses an issue, as a considerable number of SBOs not succumbing to pressure investing are distributed in years with financial adversity.

The academic discourse posits that surplus capital at the fund's life cycle's termination engenders agency conflicts as the fund is motivated to engage in unfavorable deals to maximize management fee generation (Degeorge et al., 2015). Degeorge et al. (2015) discovered that deals succumbing to pressure investing demonstrate inferior operational value creation across growth, profitability, and return measures. This conclusion intuitively aligns with the assertion that pressure SBOs essentially function as financial dissipators. The regression model output contradicts this conclusion on multiple metrics. Since several KPIs lack significance at the 5% level, it can be inferred that pressure investing does not significantly result in sub-optimal operational performance in SBOs. However, Nordic SBOs succumbing to pressure investing demonstrate superior performance on return measures such as ROIC and ROE.

8.2.2 Complementary Skills

The complementary skills hypothesis is based on existing literature, finding that complementary skills at the lead partner level are correlated with superior operational performance and deal performance relative to other buyouts (Acharya et al., 2011; Degeorge et al., 2015). The hypothesis concerning SBOs is expressed as follows.

H2(B): *"Complementary skills at the lead partner level has a positive influence on operational performance in SBOs"*

The expectation is that a buyer with complementary skills to the seller is able to enhance operational performance further. The results yielded from the regression model are displayed in table 8.3.

Table 8.3: Regression Output Research Question 2, Complimentary Skills

KPI	Sales Growth	EBITDA	ROIC	ROE	ROA	Sales/IC	FCF/IC	NIBD/ EBITDA	NIBD/FA
Complimentary Skills	0.047	0.012	-0.020	-0.087	-0.005	-0.058	-0.070	-0.536	0.042
Std. Error	0.031	0.017	0.071	0.101	0.024	0.972	0.049	1.096	0.146
Robust std. Errors	✓	✓	✓	✓	✓	✓	✓	✓	✓
P-value	0.140	0.473	0.779	0.391	0.828	0.953	0.161	0.627	0.773
R squared	0.051	0.197	0.078	0.203	0.114	0.162	0.446	0.084	0.203
N observations	54	54	54	54	54	54	54	54	54
EBITDA-margin	✗	✗	✗	✗	✗	✗	✗	✗	✗
Ln(Assets)	✗	✓	✓	✓	✓	✗	✓	✗	✗
LBO spread	✗	✓	✗	✗	✗	✓	✗	✓	✗
Capital structure	✓	✗	✗	✓	✗	✓	✓	✗	✓
Quick ratio	✗	✗	✗	✗	✗	✗	✗	✗	✓
NWC/sales	✗	✗	✗	✗	✗	✗	✗	✗	✗

Overall, the model suggests that complementary skills at the lead partner level may not be a predictor of operational performance in SBOs, explained by the lack of statistical significance. However, some interesting patterns are present in the regression output. An interesting observation is that the coefficients of return measures are negative, indicating that SBOs with complementary skills at the lead partner level exhibit inferior performance on return KPIs. At the same time, Sales CAGR and EBITDA demonstrate positive coefficients, with Sales CAGR close to significance at the 10% level. The results do not show significant evidence that complementary skill sets enhance operational performance. The sample size is critical due to the lack of available data. A larger sample size could potentially improve the model output. An important factor is the distribution of lead partners with financial and operational backgrounds, skewed toward financial backgrounds, as depicted in figure 7.6. Another important factor to consider is the time window of measurement. As the holding period often extends for more than 2 years, one can argue that it is difficult to capture the full effect of VCPs within the analyzed period. Extending the time series could yield more representable results since strategic changes might take longer to evolve.

Looking further into median values in the sample data, it is evident that SBOs with complementary skills exhibit a sales CAGR of 11%, while other SBOs exhibit a sales CAGR of 7%. Additionally, SBOs with complementary skills and other SBOs exhibit a negative EBITDA-margin expansion of -1% and -6%, respectively. Moreover, SBOs with complementary skill sets demonstrate a negative ROIC expansion of -11% compared to -14% for other SBOs. This indicates that on a median level, lead partners with complementary skills seem to outperform in sales growth, EBITDA margin, and ROIC improvement. The data upon which the regression is based shows that complementary skills have a positive influence on the highlighted KPIs. However, the limited number of observations for this hypothesis constrains the opportunity for confident inference. Despite this, it seems compelling to further explore how complementary skill sets influence KPIs with an expanded sample size.

8.2.3 Specialization

The fund-specialization hypothesis is based on the notion that specialist funds can leverage industry knowledge to implement and execute VCPs to enhance operational performance.

H2(C): *"Specialized funds experience superior operational performance in SBO deals relative to generalist funds"*

The output of the regression model is illustrated in table 8.4.

Table 8.4: Regression Output Research Question 2, Fund-Specializaion

KPI	Sales Growth	EBITDA	ROIC	ROE	ROA	Sales/IC	FCF/IC	NIBD/ EBITDA	NIBD/FA
Fund Specialization	-0.004	0.039***	0.018	0.096	0.030	0.198	0.033	-0.719	-0.137
Std. Error	0.025	0.014	0.070	0.127	0.031	0.955	0.057	0.998	0.091
Robust std. Errors	✓	✓	✓	✓	✓	✓	✓	✓	✓
P-value	0.887	0.007	0.798	0.452	0.348	0.836	0.567	0.473	0.135
R squared	0.007	0.173	0.324	0.163	0.274	0.089	0.220	0.022	0.344
N observations	102	102	102	102	102	102	102	102	102
EBITDA-margin	✗	✓	✗	✓	✗	✗	✓	✗	✗
Ln(Assets)	✗	✓	✓	✓	✓	✗	✗	✗	✗
LBO spread	✗	✗	✗	✗	✗	✗	✓	✓	✗
Capital structure	✗	✗	✓	✗	✓	✓	✓	✗	✓
Quick ratio	✗	✗	✗	✓	✗	✗	✓	✗	✗
NWC/sales	✓	✗	✗	✗	✗	✗	✗	✗	✗

The model displays an EBITDA coefficient of 0.039, implying a 3.9% EBITDA increase associated with specialized funds relative to generalist funds, assuming all other variables remain constant. This effect, statistically significant at the 1% level (p-value of 0.007), suggests that industry specialization might effectively boost profitability within the measurement timeframe. The transfer of the portfolio company from a generalist fund, potentially deficient in specific industry knowledge, to a specialized fund might explain the increased return metrics observed in SBOs. In this context, specialized funds, with their comprehensive knowledge of factors influencing valuation in exit scenarios, are likely to integrate this expertise into the portfolio company's strategic focus. This action highlights EBITDA as a key driver of valuation, which is prioritized to optimize the exit valuation scenario.

Despite the absence of statistical significance that make coefficients indistinguishable from zero, an interesting pattern surfaces from the output. Excluding Sales CAGR which is virtually zero, all return and efficiency KPIs display positive coefficients. Additionally, both debt measures show negative coefficients, furthering insights into the specialization hypothesis and enhancing the trends' coherence in the regression model associated with this hypothesis. Although it is not feasible to make conclusions about the sign of non-significant coefficients, such patterns are noteworthy. Aligned with contemporary literature to some extent, these results reveal a consistent pattern: SBO deals involving specialized funds tend to yield higher measures of profitability, return, and efficiency than those involving generalist funds.

8.2.4 Industry Specialization

In the context of the premise that specialized funds demonstrate inferior operational performance compared to SBOs, a supplementary hypothesis is formulated to account for the variations in the fund-specialization hypothesis. The criterion of more than three industry companies provides more evenly distributed data, as discussed in chapter 7 on descriptive statistics.

H2(D): *"Funds with industry experience exhibit superior operational performance in SBO deals relative to generalist funds"*

The expectations are the same as the fund specialization hypothesis. The regression output is displayed in table 8.5.

Table 8.5: Regression Output Research Question 2, Industry Specialization

KPI	Sales Growth	EBITDA	ROIC	ROE	ROA	Sales/IC	FCF/IC	NIBD/ EBITDA	NIBD/FA
Industry Specialization	-0.040	0.010	-0.039	-0.104	0.009	-0.268	0.028	-0.555	-0.101
Std. Error	0.024	0.015	0.059	0.095	0.019	0.713	0.039	0.748	0.098
Robust std. Errors	✓	✓	✓	✓	✓	✓	✓	✓	✓
P-value	0.105	0.528	0.516	0.273	0.629	0.708	0.472	0.460	0.306
R squared	0.034	0.129	0.327	0.168	0.263	0.090	0.220	0.063	0.343
N observations	102	102	102	102	102	102	102	102	102
EBITDA-margin	✗	✓	✗	✓	✗	✗	✓	✗	✗
Ln(Assets)	✗	✓	✓	✓	✓	✗	✗	✓	✗
LBO spread	✗	✗	✗	✗	✗	✗	✓	✓	✗
Capital structure	✗	✗	✓	✗	✓	✓	✓	✓	✓
Quick ratio	✓	✗	✗	✓	✗	✗	✓	✗	✗
NWC/sales	✗	✗	✗	✗	✗	✗	✗	✗	✗

Negative coefficients are observed for Sales CAGR, ROIC, ROE, Sales/IC, NIBD/EBITDA, and NIBD/FA, implying that funds with industry specialization possess lower values on these metrics. Nevertheless, the p-values associated with these coefficients fall in the non-significant territory. For EBITDA, ROA, and FCF/IC, the coefficients are positive, suggesting that industry-specialized funds may perform better on these metrics. However, the p-values are also non-significant. Given the inconclusive results and lack of significance, it would not be appropriate to draw definitive inferences about the impact of having more than three prior industry portfolio companies on operating performance.

Interestingly, negative coefficients contradict the expectation that funds concentrated in specific industries, presumed to have superior industry knowledge, would display superior operational performance.

A deeper examination of underlying median values in the SBO sample reveals that industry specialization does not appear to yield substantial differences. For instance, sales CAGR is 7% compared to 8% for non-industry specialized funds. There is a marginal difference in the EBITDA measure, and industry-specialized funds register a change of ROIC during the measurement timeframe of -15% against -12%. Median values in the SBO sample suggest that specialized funds tend to experience a less negative expansion in ROIC during the initial two years of the holding period. Concurrently, leverage levels are similar for both groups. Nonetheless, the criterion of having more than three portfolio companies in the same industry might not serve as a reliable predictor of industry specialization, which could explain the absence of statistical significance in the results.

8.2.5 CEO Replacement

The results on management replacement are based on hypothesis H2(E), which is inspired by the consensus in the literature that CEO replacement enhances operational performance (Gong & Wu, 2011; Guo et al., 2009).

H2(E): *"CEO replacement has a positive impact on SBOs' operating performance"*

Aligned with Gong and Wu (2011), CEO replacement is an inherent tool in VCPs, actively used by PE funds to assign competent CEOs to portfolio companies (Bennedsen et al., 2008). Within the first year of the holding period, 33% of CEOs in the SBO sample were replaced, lower than the 51% replacement rate found in Gong and Wu's study on LBOs (Gong & Wu, 2011). The analysis presents conflicting conclusions on several KPIs, showing mostly negative effects when the CEO is replaced within the first year. The only statistically significant finding, NIBD/EBITDA at the 10% level, suggests a positive correlation between CEO replacement and higher leverage in SBO deals.

Table 8.6: Regression Output Research Question 2, CEO Replacement

KPI	Sales Growth	EBITDA	ROIC	ROE	ROA	Sales/IC	FCF/IC	NIBD/ EBITDA	NIBD/FA
CEO Replacement	0.027	-0.010	0.049	0.007	-0.013	-0.885	-0.046	1.663*	0.040
Std. Error	0.026	0.018	0.059	0.095	0.019	0.601	0.043	0.870	0.114
Robust std. Errors	✓	✓	✓	✓	✓	✓	✓	✓	✓
P-value	0.288	0.586	0.404	0.944	0.479	0.144	0.290	0.059	0.726
R squared	0.018	0.129	0.009	0.106	0.200	0.103	0.136	0.077	0.003
N observations	102	102	102	102	102	102	102	102	102
EBITDA-margin	✗	✓	✓	✗	✓	✗	✗	✓	✗
Ln(Assets)	✗	✗	✗	✓	✓	✗	✓	✗	✗
LBO spread	✗	✗	✗	✗	✗	✗	✗	✓	✓
Capital structure	✗	✗	✗	✓	✗	✓	✓	✓	✗
Quick ratio	✓	✗	✗	✗	✓	✗	✗	✗	✗
NWC/sales	✓	✗	✗	✗	✗	✗	✗	✓	✗

The coefficient for Sales/IC, a measure of capital productivity, is estimated to be -0.885, indicating that SBOs undergoing CEO replacement experience a contraction in this measure. However, given the lack of statistical significance, these results warrant cautious interpretation.

Examining the underlying median expansion values, it is observed that SBOs experiencing CEO replacement have an 11% Sales CAGR and a median EBITDA of -3.8%, highlighting a trend toward sales growth over profitability. Furthermore, these SBOs show a lower ROIC expansion and a heightened NIBD/EBITDA compared to their counterparts, illustrating the complexity of leadership transitions on financial performance indicators.

R-squared values for all regressions are low, suggesting limited explanatory power of the model. Surprisingly, the EBITDA measure reveals a negative coefficient of -0.01, implying that new CEOs fail to enhance the EBITDA margin. Unlike other studies (Foldager & Mølbak, 2020; Skibsted & Thelin, 2018), return measures display positive coefficients, excluding ROA.

The statistically insignificant results suggest that CEO replacement does not immediately impact performance indicators due to factors such as time lag, existing corporate strategy, and a single individual's influence (Plenborg & Kinserdal, 2021). Moreover, new CEOs may implement restructuring involving non-core entities' divestment, potentially skewing the results.

In conclusion, the regression model indicates that CEO replacements do not significantly affect short-term operational performance in SBOs, contradicting existing literature on operational value creation in SBOs.

8.2.6 Fund Size

Existing literature presents mixed results regarding the impact of fund size on returns measured through IRR. For instance, Humphery-Jenner (2012) associates larger PE firms with a higher IRR, while Harris et al. (2014) and Lopez-de-Silanes et al. (2014) find no significant correlation between fund size and returns. Given these inconsistencies, the hypothesis predicts a positive influence of fund size on operating performance, assumed to correlate with returns.

H2(F): *"Fund size has a positive influence on operating performance in SBOs"*

The results yielded from the regression model are displayed in table 8.7.

Table 8.7: Regression Output Research Question 2, Fund Size

KPI	Sales Growth	EBITDA	ROIC	ROE	ROA	Sales/IC	FCF/IC	NIBD/ EBITDA	NIBD/FA
Fund Size < 300	0.100	0.037	-0.161	-0.046	-0.043	-0.804	-0.118	2.708	0.568
Fund Size 300-1000	0.144	0.026	-0.229	-0.111	-0.063	-1.767	-0.069	3.154	0.441
Fund Size 1000-3000	0.084	0.050	-0.106	0.000	-0.041	-1.732	0.012	3.298	0.515
Fund Size 3000-5000	0.167	-0.020	-0.346	-0.197	-0.125	-3.877**	-0.069	4.690	0.499
Fund Size > 5000	0.099	0.009	-0.257	-0.087	-0.079	-1.932	0.022	5.057	0.724
Robust std. Errors	✓	✓	✓	✓	✓	✓	✓	✓	✓
R squared	0.066	0.201	0.375	0.172	0.314	0.157	0.223	0.064	0.37
N observations	103	103	103	103	103	103	103	103	103
EBITDA-margin	✓	✓	✗	✓	✗	✗	✗	✗	✗
Ln(Assets)	✓	✓	✓	✓	✓	✓	✗	✗	✗
LBO spread	✓	✗	✗	✗	✗	✗	✓	✓	✗
Capital structure	✓	✗	✗	✗	✓	✓	✓	✗	✓
Quick ratio	✗	✗	✗	✓	✗	✗	✓	✗	✗
NWC/sales	✗	✗	✗	✗	✗	✗	✗	✗	✓

While many researchers employ PE firm AuM, this study uses fund size, correlating with firm size (Stowell, 2018). The regression model results show positive coefficients for most growth and profitability measures, except for the fourth category and EBITDA ME. However, returns measures are negative, conflicting with the anticipation that large PE funds, coupled with capital availability, enable organic and inorganic top-line growth scaling.

A notable observation involves larger funds, particularly those between 3000-5000 mEUR, demonstrating a statistically significant negative coefficient for Sales/IC at the 5% level. This suggests these funds are less efficient in generating sales from invested capital. Nevertheless, outliers in the SBO sample seem to drive this conclusion, while the skewed distribution of observations towards smaller funds influences the regression model output.

Extant literature reveals a positive correlation between fund size and leverage levels, suggesting that larger funds may use increased leverage in top-line growth strategies due to enhanced access to financing (Stowell, 2018). This pattern underscores the interaction between fund size, access to financing, and strategic leverage use in growth financing.

8.2.7 Lead Partner Experience

The hypothesis concerning lead partner experience suggests that increased experience at this level enhances operational performance. Studies indicate that skills at the lead partner level positively affect buyout returns (Acharya et al., 2011; Loos, 2006) and operational value creation (Amess & Wright, 2013). The hypothesis is formulated as follows.

H2(G): *"Lead partner experience positively influences operational performance in SBOs"*

Anticipated findings, based on existing literature, propose a correlation between lead partner experience and superior operational performance. Regression model results are displayed in table 8.8.

Table 8.8: Regression Output Research Question 2, Lead Partner Experience

KPI	Sales Growth	EBITDA	ROIC	ROE	ROA	Sales/IC	FCF/IC	NIBD/ EBITDA	NIBD/FA
Lead Partner Experience < 1	0.144**	0.025	-0.221	-0.128	-0.070***	-2.600**	-0.040	3.677	0.609
Lead Partner Experience < 3	0.141**	0.027	-0.173	-0.058	-0.060***	-1.102	-0.043	3.458	0.630
Lead Partner Experience < 8	0.116	0.030	-0.161	0.015	-0.043	-1.642	0.020	3.823	0.715
Lead Partner Experience > 9	0.102	0.042	-0.234	-0.161	-0.057**	-0.533	0.053	3.124	0.509
Robust std. Errors	✓	✓	✓	✓	✓	✓	✓	✓	✓
R squared	0.035	0.133	0.333	0.175	0.270	0.133	0.250	0.067	0.354
N observations	103	103	103	103	103	103	103	103	103
EBITDA-margin	✗	✓	✗	✓	✗	✗	✓	✗	✗
Quick ratio	✗	✓	✓	✓	✓	✗	✗	✓	✗
LBO spread	✗	✗	✗	✗	✗	✗	✓	✓	✗
Capital structure	✗	✗	✓	✗	✓	✓	✓	✓	✓
Quick ratio	✗	✗	✗	✓	✗	✗	✓	✗	✗
NWC/sales	✓	✗	✗	✗	✗	✗	✗	✗	✗

Sales CAGR coefficients suggest less experienced lead partners (< 1 year and < 3 years) pursue aggressive growth strategies, resulting in a higher Sales CAGR. However, as experience surpasses 3 years, Sales CAGR decreases, indicating a strategy shift towards sustainable growth. Less experienced groups demonstrate the highest sales CAGR, supported by statistical significance at the 5% level.
EBITDA coefficients increase with the experience level, suggesting more experienced partners improve profitability in SBOs more proficiently, although this lacks significance. Return measures exhibit negative coefficients, except for ROE in the < 8 category. A notable negative effect in less experienced categories might suggest riskier investments without proportional asset productivity.

Efficiency measures, such as Sales/IC, are notably negative and significant for funds with lead partners of less than one deal of experience, indicating less efficient sales generation from invested capital. As experience increases, so does the coefficient, suggesting superior sales generation.

The relationship between lead partner experience and operational performance appears nuanced and dependent on the specific operational performance metric. While results align with Amess and Wright (2013) show positive trends in efficiency measures, these are less efficient than the peer group. Contrary to Gilligan and Wright (2020), the results do not suggest that more experienced lead partners necessarily have access to superior deals, as inferred from the operating metrics. Given the mixed results, it's challenging to definitively conclude the uniform operational performance enhancement by lead partner experience.

8.3 Summary of Results

This section provides a summarization and deduction of insights from the findings of the regression model and its underlying data. As the methodology chapter highlights, operational value creation, due to its complexity, is elucidated through five distinct metrics. Table 8.9 provides a concise summary of the regression coefficients connected to the specific KPI of the related hypotheses.

Table 8.9: Hypothesis Performance Evaluation

H	Hypothesis	Exp.	Realized	Growth	Profitability	Return	Efficiency	Debt
H1	SBOs vs. PBOs	-	±	-	+	+	±	-***
H2(A)	Pressure Investing	-	+	+	-	+***	+	-
H2(B)	Complementary Skills	+	+	+	+	-	-	-
H2(C)	Specialized Fund	+	+	-	+***	+	+	-
H2(D)	Industry Specialization	+	-	-	+	-	±	-
H2(E)	CEO Replacement	+	+	+	-	+	-	+*
H2(F)	Fund Size	+	±	±	-	±**	+	
H2(G)	Lead Partner Experience	+	±	-**	+	±***	±**	±

Exp. denotes the expected outcome (sign) for the hypothesis prior to the analysis. The expected sign aggregates all 5 metrics into one overall expectation.
Realized' denotes the collection of the actual signs, as determined in each of the five categories through the analysis results.
Significance at the 10%, 5% and 1% level is denoted by *, ** and *** respectively.
+ Denotes the coefficient(s) in the regression being positive.
- Denotes the coefficient(s) in the regression being negative.
± Denotes the coefficient(s) in the regression point in both direction.

Research Question 1 (H1)
PBOs manifest superior growth, while SBOs excel in profitability and return measures. This negative correlation between growth and profitability/returns emerges in the data analysis, illuminating the inescapable trade-off inherent to divergent operational strategies, even with PE ownership. Efficiency presents a mixed picture, with some evidence suggesting superior capital efficiency for SBOs, and some favoring PBOs.
Regarding indebtedness, SBOs demonstrably shoulder greater leverage. Nonetheless, the only significant finding from the regression analysis pertains to SBOs registering markedly lower NIBD/FA. This disparity is plausibly due to PE firms' proficiency in leveraging a smaller fixed asset base, in contrast to larger SBOs.
Summarily, evidence suggests both inferior and superior operational performance in SBOs, leading to the adoption of a ± sign in Table 8.9 to represent this ambiguity. For a definitive conclusion, it is necessary to determine, through assumptions or empirical evidence, which changes in operating performance generate the highest value creation.

H2(A) suggests that investing under pressure, marked by inherent uncertainty and decision-making implications, may yield sub-optimal performance. However, the realized sign across all five metrics in aggregate contradicts this, indicating pressure investing as a positive determinant for performance. The coefficients for both growth and profitability are indistinguishable from zero. Yet, in the return measures, the presence of highly significant coefficients becomes apparent. This highlights that SBOs acquired under conditions of pressure generate significantly higher AOPs compared to those investments not subjected to pressure investing.

H2(B) hypothesized that the presence of complementary skills at the lead partner level would enhance performance. The regression model's coefficients confirm this for growth and profitability in companies. Conversely, return, efficiency, and debt measures are negatively influenced. Although positive outcomes arise in only two of three measures, the realized sign is positive due to the near significance of growth and because growth and profitability are viewed to outweigh efficiency and debt measures when considering operational performance. Therefore, the analysis suggests that complementary skills offer some positive impact on operating performance. However, given the lack of statistical evidence and inherent ambiguity, these results warrant cautious interpretation.

H2(C) yields results indicating that fund specialization is the most influential positive driver of operating performance. The coefficient associated with growth is virtually zero, while the profitability and all return and efficiency measures consistently produce positive coefficients. This data serves as compelling evidence that specialized funds contribute to operating performance in SBOs. The significance of EBITDA at the 1% level further bolsters the confidence in this assertion. Thus, specialized funds have been shown to foster superior operating performance compared to alternative strategies.

H2(D) designated as the PE firm with three or more companies in the same industry, was anticipated to bolster operating performance. However, evidence contradicts this hypothesis, and the results remain ambiguous. The irregularity of coefficients and lack of statistical significance renders conclusive interpretation of the results challenging.

H2(E) the replacement of a CEO within the first year of ownership appears to influence growth, return, and debt metrics on an upward trajectory while negatively impacting efficiency. The coefficient related to EBITDA stays close to zero, rendering it less crucial when aggregating the results. A slight significance emerges with the CEO creating excess leverage based on the company's EBITDA. An overall interpretation of the analysis results suggests that CEO replacement positively influences operating performance. However, due to the absence of statistical significance, caution is recommended when drawing inferences.

H2(F) investigating fund size proves intuitive, as a prevailing bias suggests that large fundraising rounds correlate with investor confidence, typically bolstered by a successful track record. Thus, the hypothesis asserted that sizable funds capable of excessive fundraising should possess the ability to stimulate superior operational performance. However, the regression analysis lacks sufficient clarity, indicating no discernible correlation between fund size and operating performance within the sampled population.

H2(G) partners of high approval secure leadership roles in numerous companies due to their value-creating contribution. A hypothesized correlation existed between such extensive experience and an enhancement in operating performance. Yet, the evidence, in its current state, remains inconclusive. Fluctuating coefficients and a lack of rigor in the results preclude a robust conclusion about the definitive impact of extensive partner experience on operational value, whether superior or inferior.

9.0 Discussion

This chapter delves into various aspects of the conducted analysis, particularly relating to methodology. It scrutinizes the validity and reliability of the results to determine how representative they are of the outcomes derived from the regression analysis. A broader discussion of the findings will follow this. The implications of the results will be deliberated upon subsequently, leading to suggestions for potential future research.

9.1 Validity of Results

Validity is a fundamental concept in research methodology, defining the degree to which a test or instrument accurately measures what it purports to measure. Without validity, the results of a study may be misleading or lack meaning, regardless of how groundbreaking they may appear. This concept is essential in establishing the veracity and credibility of research findings.
Different forms of validity act as crucial quality control mechanisms in research design. They assess diverse aspects, from assessment content's relevance to research findings' generalizability. Ensuring these validity forms enhances the reliability, value, and impact of the knowledge produced in any research field (Trochim & Donnelly, 2006).

Multicollinearity
In conducting the regression analysis for this study, potential issues of multicollinearity were examined. Multicollinearity is a circumstance where two or more predictor variables in an OLS regression model are highly correlated, making it difficult to estimate and interpret the regression coefficients accurately.
To determine the presence and extent of multicollinearity, a correlation matrix was generated for all predictor variables. The correlation matrix is a useful tool as it provides a measure of the degree of linear association between pairs of variables. Each cell in the matrix displays the correlation coefficient for a pair of variables, ranging between -1 and +1. A coefficient close to +1 or -1 suggests a strong positive or negative correlation, respectively, and can potentially indicate multicollinearity if these variables are used together in the regression model.

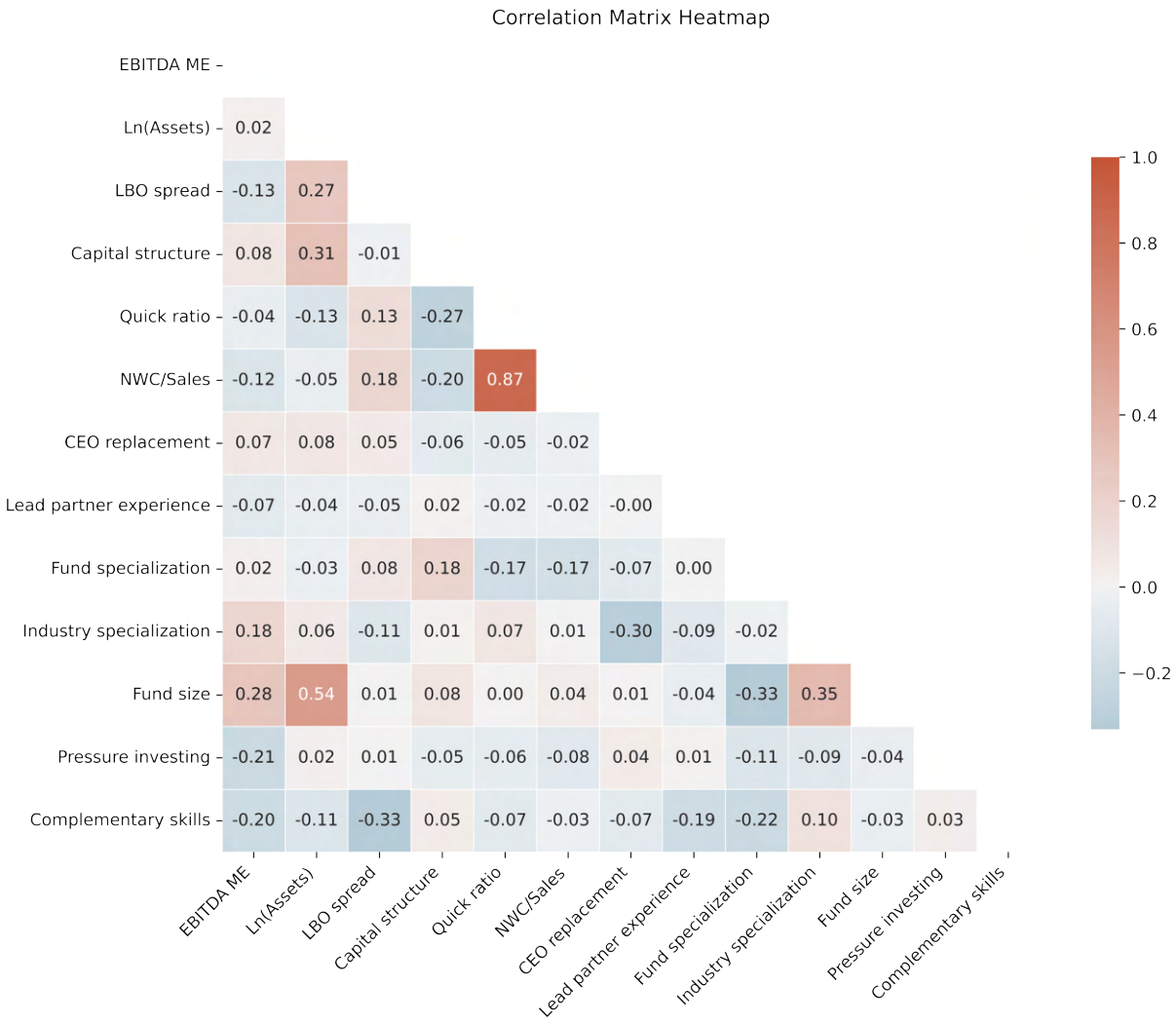


Figure 9.1: Correlation Matrix Heatmap, Between All Explanatory- & Control Variables

As shown in the matrix, the correlation between coefficients is peaking at ± 30-35%. However, two are more pronounced, indicating a strong positive correlation. This could potentially lead to multicollinearity if both variables were included in the same regression model.
The observed correlations necessitated addressing potential multicollinearity. This was mitigated by excluding overlapping explanatory variables, such as LN(Assets) in the fund size hypothesis, from the model, thereby preserving the validity of the OLS regression model. Upon implementing these modifications, the revised model demonstrates enhanced stability and interpretability.

Heteroskedasticity
Given the inherent volatility of financial data, the models exhibited heteroskedasticity. To counteract its potential impact and preserve the reliability of the results, heteroskedastic-robust standard errors, detailed in chapter 6, were applied. This approach effectively safeguarded the validity of the outcomes. The complete regression results employing these robust standard errors can be found in Appendix F.
By utilizing these heteroskedastic-robust standard errors, the final model accounts for potential heteroskedasticity, ensuring the validity of the results despite the violation of the homoscedasticity assumption.

Linearity and Autocorrelation

The linearity assumption postulates a linear relationship between the independent and dependent variables. This criterion is inherently satisfied when employing dummy variables, as these are linear by their nature.

On the other hand, the absence of autocorrelation is vital for sound inference from the model's output. Autocorrelation implies that the residuals, or error terms, are not independent of each other, which can lead to inaccurate standard errors and inefficient estimates.

The Durbin-Watson test, used to detect autocorrelation, produced values near two for all regression analyses in this study, thereby satisfying the assumption of no autocorrelation.

Winsorizing Data

In this thesis, winsorization was utilized to tackle the presence of significant outliers in our dataset. By capping the extreme values at the 5% and 95% percentiles, we could curtail the undue influence of outliers on the analysis, thereby enhancing the validity of the findings.

A crucial aspect of this decision was the maintenance of the statistical power of our analysis. Unlike deletion, winsorization does not eliminate any data points, which prevents any reduction in the power or generalizability of our results, ensuring external validity.

Moreover, selecting a 5% threshold for winsorization was a balancing act between reducing outlier impact and preserving as much original data as possible. This approach, endorsed in academic research, preserves the internal validity of the thesis by keeping data manipulation to a minimum (Rousseeuw & Hubert, 2018). Despite criticisms such as potential bias introduction and data alteration, the validity gained through a more representative mean and reduced outlier influence outweighs the minor alterations to extreme data values (Wilcox, 2017). Therefore, winsorization was instrumental in not only managing outliers effectively but also maintaining the validity and reliability of our findings.

Time Series of Measurement

The outcomes derived from the models and data utilized in this research are significantly influenced by the selected time horizon and performance measurement method. It's evident upon analysis that the chosen examination period may be subject to debate due to various identified constraints.

First, the prioritization of margin expansion measurements may overlook cash flow, earnings, or efficiency in intermediate years, potentially skewing performance portrayal throughout the research timeline.

Second, the expansion metrics used are subject to mechanical effects due to certain factors. PE funds typically target mature businesses that exhibit stable growth and earnings (Biesinger et al., 2020), traits that significantly affect the metric. As dashboard (1/2) shows, the year before the PBO often displays high margins at a sample level. The transaction year incites considerable changes in the companies' financial composition, triggering variations in financial metrics. This "noise" during the transaction thereby compromises the short-term measurement of the chosen performance KPI. Furthermore, efforts to increase already high initial margins can pose a challenge, unlike scenarios starting from lower margins, impacting results in both samples.

Lastly, the assertion that examining value creation in terms of operating performance necessitates a longer time frame holds merit. Portfolio companies are often held longer than the duration measured in this study, and the implementation of value-creating strategies typically requires an extended time period. This observation underscores the potential advantage of examining the full ownership duration or as many years as possible, offering a comprehensive view of operating performance and a robust evaluation of the value creation in the SBO or PBO.

9.2 Reliability

Financial Data

The confidentiality of PE funds and associated companies considerably constraints this thesis, specifically regarding financial data access. Initially, financial data were extracted from databases such as Valu8, Capital IQ, Preqin, and Orbis. Due to observed inconsistencies across these sources, a decision was made to manually collect all financial data, despite the risk of typographical errors. The reliability of the financial data was assured through cross-verification. Therefore, manual data collection is viewed as more reliable than database-extracted financials.

The calculations of ROIC and NIBD influence the reliability of the results. For instance, the ROIC calculation, which includes an average corporate tax rate of the analyzed countries, introduces some uncertainty due to varying tax rates in the Nordics.

Intra-group loans, observed in both samples and associated with transfer pricing practices, were recognized in the thesis. These were not adjusted according to each year's respective intra-group loan practices within the time series, introducing some uncertainty into the NIBD measure. However, excluding intra-group loans would bias the NIBD measure downward.

The recognition of shareholder loans as debt may be disputed, as they can also be viewed as extended equity financing. This recognition in NIBD could introduce an upward bias to ROE. The inclusion of leases, especially before adopting IFRS (16), presents another potential pitfall, as leases were categorized into operational and financial leasing.

Normalization of financial data, including fiscal year adjustments, significantly influences the reliability of dependent variable analysis. This process allows for accurate comparisons across varying periods and companies. However, potential inaccuracies may arise due to underlying assumptions, subtly adding variance to the data and impacting the reliability of the regression model. For instance, the normalization process overlooks the seasonality of sales and earnings, which could bias the normalized measures and affect the findings' reliability and interpretability. The issue of data normalization extends to free cash flow (FCF) measures in this analysis. Investing and financing activities are not normalized, potentially introducing bias. This non-normalization might distort the true FCF measures due to a deficiency of cash flows from operations. This decision was made to avoid affecting FCF because of substantial variation in investing and financing activities when the PE owner takes over. However, while income statement items in the cash flow statement have been normalized, keeping investing and financing activities unadjusted might skew the sample data. This could impact the reliability and validity of the findings.

AOP Measures and Industry-Matching

The industry-matching principle in this study adjusts for time- and industry-specific effects. However, its potential for disregarding significant firm-specific attributes when forming the comparison group is limited. An alternative, the direct matching principle, forms a directly comparable peer group for all observations but faces challenges in identifying suitable peers and dealing with financial data availability.

Efficiency of the industry-matching principle can be improved by introducing additional criteria, following Bonini (2015). A size criterion, allowing peer firms to vary by ± 50% of total assets, ensures uniformity and comparability. Equivalent criteria may apply to financial measures like revenue and profitability. Another option is the least sum of absolute rank differences (SARD) method, focusing on similarity in financial metrics, properties and outlook.

However, the precision of the comparison group and the industry-matching principle's quality are debatable. The comparison group mostly comprises publicly traded companies due to their superior financial data. This composition may introduce survivorship bias, as these companies often represent top-performing corporations. Incorporating smaller, private, non-PE-backed firms could provide a more representative benchmark for AOP calculations, but it may risk compromising financial data quality. Another concern is the possible steady state of growth and profitability in larger, publicly traded companies (Plenborg & Kinserdal, 2021), leading to lower expansion measures and potential bias in results.
Lastly, the choice of peers may significantly impact results. For example, smaller firms with available financial resources from PE funds may find it easier to increase sales and profitability, introducing an upward bias in AOP measures. However, firms that employ buy-and-build strategies are prone to accumulate substantial goodwill items on their balance sheet, which introduces a downward bias in measures affected by a larger asset base.

9.3 Limitations

Upon sharing the results and critically assessing their validity, the constraints within the thesis methodology need examination. This includes investigating limitations in the data collection process and analyzing the methodological approach of the thesis.

Sampling Limitations
The creation of the data sample met multiple challenges. The PBO sample, derived from the SBO sample, incorporated industry criteria and a ± one-year temporal boundary, aiming for equitable observation distribution. The PBO sample shows a left-skewed distribution, with an over-representation of recent year observations, which is not ideal and can introduce bias. Industry matching might offset this skewness, yet it remains a potential issue. Furthermore, the unequal distribution of transactions across the Nordic countries is evident in the high proportion of Swedish. This disparity also potentially skews the distribution across FF10 industry clusters, given industry composition varies for the analyzed countries.

Financial Data Collection Limitations
The confidentiality of PE funds and their portfolio companies restricts access to financial data, introducing uncertainty. The unavailability of financial statements from parent companies outside the Nordic region further compounds this issue. A secondary challenge is the possible change in fiscal years during the transaction year. Although normalizing income statement items can mitigate this, it may introduce bias, thus affecting the findings' robustness.

9.4 Discussion of Findings

This subsection will present a thorough discourse of the analysis outcomes juxtaposed with the extant literature and overarching theory. It further probes those findings that contradict the current literature, offering an exploration of such discrepancies.

9.4.1 Operational Performance in SBOs vs. PBOs

The initial expectation was that SBOs exhibit inferior performance in all KPIs but those related to debt. The analysis reveals that PBOs exhibit an elevated degree of abnormal sales growth in comparison to SBOs. Nonetheless, the asserted inferior sales growth lacks compelling statistical significance. Despite this, the finding

is in alignment with extant literature (Bonini, 2015; Foldager & Mølbak, 2020; Freelink & Volosovych, 2012; Skibsted & Thelin, 2018). The regression model unveils an enhancement in the EBITDA margin expansion for SBOs relative to PBOs, albeit the absence of statistical significance. Notably, this result diverges from the entrenched academic consensus that advocates for a superior EBITDA margin expansion in PBOs (Bonini, 2015; Freelink & Volosovych, 2012; Skibsted & Thelin, 2018).
The same contrarian trend is evident in all return measures, which similarly do not attain statistical significance. Consequently, the coefficients were indistinguishable from zero. However, an emerging pattern is discernible in the discrepancy of the coefficients between sales growth, profitability and return measures. This pattern finds theoretical support from Koller et al. (2020), who argue for the trade-off between growth and profitability/margins. PE funds face a choice between VCPs that yield immediate returns and those that foster long-term value-creation. For example, lead partners might elect an aggressive growth strategy, necessitating substantial costs which subsequently suppress the margins. Inorganic growth strategies such as buy-and-build or other forms of inorganic growth result in cost capitalization, thereby suppressing short-term profitability and return measures (Koller et al., 2020). In light of this, the regression analyses conducted in response to the first research question validate the existence of this trade-off. As observed, PBOs tend to prioritize growth, which could suggest a natural transition for SBOs to concentrate on margins and returns. Empirically a high growth business creates more value by increasing ROIC and low ROIC companies create more by increasing ROIC (Koller et al., 2020). Our data in (Dashboard 1/2) seem to support this, indicating high starting ROIC for both buyouts, thereby making a focus on top-line growth a clear or logical choice, from a value creation standpoint. If PBOs typically maintain high growth rates throughout the ownership period, it could be more advantageous for SBOs to focus on ROIC and margins. The regression result could suggest such a dynamic between growth and ROIC for buyouts, and PE owners are aware of this in their VCPs. This could support that findings show PBOs grow more and SBOs achieve higher expansion in profitability and returns across all measured KPIs.

The significantly lower FCF/IC expansion aligns with initial expectations of better PBO performance. Dashboard (2/2) shows the median FCF/IC ratio for SBOs quadrupling that of PBOs pre-transaction. Despite our expansion measure not accounting the intermediate year, it's improbable for SBOs to increase this measure due to their high starting point. This explains the negative coefficient for SBOs, consistent with the ratio's trend in the initial post-acquisition years.

Despite conventional wisdom suggesting that SBOs exhibit higher leverage than PBOs, the results from this research add nuance to this understanding. In absolute terms, SBOs agree with traditional findings, however, a more relative assessment of leverage tells a contrasting story. SBOs demonstrate a lower NIBD/FA ratio than PBOs, an observation that holds substantial statistical significance and propounds an alternate viewpoint on leverage when fixed assets are taken into consideration.
This apparent contradiction could be influenced by the decision to incorporate goodwill into fixed assets, a move that could notably affect the ratio's denominator. This effect is likely to be pronounced in instances where buy-and-build strategies are employed. Upon examining the SBO sample, such strategies were observed in approximately 30% of the cases, which would influence the denominator in the SBO-related ratio. This prevalence of buy-and-build cases supports the concept that PE funds can increase leverage relative to a smaller nominal fixed asset base more actively. Moreover, as evident from Table 7.1, the mean NIBD/FA values are substantially different, with a high magnitude, providing further backing for arguments regarding PBOs' ability to leverage the fixed asset base. However, the limitations of this research did not permit a similar scrutiny of buy-and-build cases within the PBO sample.
Concerning the overall leverage in the capital structure across both samples, Dashboard (2/2) presents an

interesting observation. The median leverage levels of Scandinavian SBOs and PBOs refute the theoretical ceiling of approximately 70% postulated in existing literature (Berk & DeMarzo, 2020; Rosenbaum & Pearl, 2009), instead averaging around 55% for SBOs and 50% for PBOs. Given the crucial role that leverage plays in financial engineering, it would be expected for the debt component to approach the suggested upper limit, especially for SBOs where the debt component is typically higher prior to the transaction. This divergence between theoretical expectations and actual observations offers promising avenues for future research.

9.4.2 Drivers of Operational Value Creation in SBOs

Unexpectedly, the pressure investing hypothesis showed superior growth in return measures for pressure SBOs. ROIC and ROE showed positive coefficients, contrasting Wang (2012) findings of inferior performance in pressure deals. The reasons behind these surprising results are unknown. However, it could be argued that 3.5 years post-fund vintages may not induce enough pressure to fully capture these dynamics due to limited observations beyond this point. It suggests PE funds make their most substantial investments in the initial investment phase. The skewed buyout distribution depicted in figure 7.4 could inflate AOP measures in pressure SBOs, as such, transactions in the sample occur during robust capital market periods.

Interestingly, the complementary skills hypothesis, contrary to existing literature Acharya et al. (2011) and Degeorge et al. (2015), did not produce statistically significant results. A plausible explanation could be the small sample size of 54 observations, potentially insufficient for conclusive insights on improved operational performance, attributable to limited data availability.

Contrarily, the hypothesis concerning fund specialization exhibited a statistically significant positive coefficient on EBITDA margin expansion of 3.9%. This finding implies that specialized funds prioritize and exhibit greater proficiency in enhancing profitability in SBO deals. One might speculate that specialized funds might possess the capacity to exploit readily available opportunities that remained untapped during the initial buyout. On the other hand, industry specialization yielded no statistically significant results. The "+3" criteria may not adequately represent industry specialization, and numerous scholars argue that PE firms are increasingly focusing on diverse human capital, thus enabling them to specialize across multiple industries (Rosenbaum & Pearl, 2009).

The NIBD/EBITDA ratio was the only statistically significant result linked to the CEO replacement hypothesis, indicating a significant increase in leverage relative to EBITDA when a new CEO steps in. It's challenging to fully evaluate the influence of a new CEO's VCPs in the first two years, especially when the CEO replacement occurs near the end of year one. This makes the financial impact assessment more complicated as financial metrics usually follow strategic actions (Plenborg & Kinserdal, 2021). It's also crucial to take into account the "big bath" accounting practice. New CEOs may skew initial financial reports to show decreased performance, creating a lower benchmark to boost perceived improvements in subsequent years. While no clear evidence of big baths was found in our study, it is worth noting this tactic usually needs a full annual report cycle to fully manifest, allowing for more positive subsequent performance reports. The big bath phenomenon may also cause a downward bias in expansion metrics, especially when these are calculated over a brief period ending two years post-transaction. This bias could be exacerbated if the CEO replacement happens late in the first year, potentially intensifying the negative effect on financial metrics in the second year.

Financial metrics in the short term exhibit unpredictable changes, dictated primarily by specific characteristics of the portfolio company and its competitive edge. Additionally, the period of PE ownership usually spans beyond the analyzed two-year period, indicating that full implementation and realization of VCPs demand a longer period. Therefore, it may be inferred that reaping the benefits of these strategies might necessitate a more extended timeline than initially examined, as noted in the section concerning measurement time series. This highlights the intricate nature of the matter and the requirement for future studies to fully comprehend the involved dynamics.

9.5 Future Research Directions: Reflecting Retrospectively

This section leverages experiences and insights gained during an in-depth thesis study. It aims to furnish future researchers with a comprehensive framework for understanding the intricacies of comparing SBOs and PBOs.

Analyzing Time Series Data
Investigating value creation within operational performance constraints due to limited data accessibility. The confidential nature of PE fund returns renders them unobservable without direct access to fund investor pages or related fundraising memoranda. However, operating performance analysis offers significant investigative opportunities. Reflecting on this, the [-1 : +2] approach exhibits limitations in evaluating true operational performance and, consequently, value creation. A replication of this study using financial data spanning the entire ownership period could yield meaningful insights. Moreover, considering the full ownership duration may allow for an intriguing exploration of intermediate years' inclusion, as value generation spans the entire ownership period.

Tax Specialization and Finance
An Intersection The study noted a high incidence of negative net income during periods of PE ownership. An interesting line of inquiry could be the potential for value creation in carried forward deficits. The idea presented is that this could be a value creation source, given the time-bound nature of PE ownership. Thus, a blend of knowledge in financial reporting and tax laws, along with adequate financial capabilities, could shed light on this observation. This could further enhance the understanding of another mechanism of value creation utilized by PE sponsors.

10.0 Concluding Remarks

Standing atop the metaphorical mountain of this project provides a panoramic view of the operating dynamics associated with Scandinavian private equity. The study dove deeply into the intricacies of the private equity toolbox and the underlying value-creation plans (VCPs). Together with a thorough review of existing literature, these efforts established a robust groundwork for scrutinizing the research questions. The primary focus of this thesis was to investigate two aspects related to SBOs and their operational performance compared to PBOs. Firstly, the study explored whether SBOs demonstrate inferior operational performance relative to PBOs. Secondly, the thesis conducted an in-depth analysis of how various factors from the private equity toolbox and determinants identified in existing literature influences the operational performance of SBOs.

The study's methodological approach emphasized the enhancement of data quality. The data was meticulously hand-collected, ensuring the reliability of the findings. Simultaneously, the study worked to control the influence of market effects on operating performance. This was achieved through refining the change measures in the samples evaluated from one year preceding to two years following the transaction. This method of isolating market noise in terms of systematic risk resulted in the emergence of abnormal operating performance (AOP) metrics. To delve into the research questions, OLS-regression was employed on selected KPIs to probe for statistical differences. Metrics from diverse categories such as growth, profitability, return, efficiency, and debt were chosen, providing nuanced insights and a comprehensive view on operational value creation.

The first research question engaged with comparing the operational value-creation capacities of SBOs and PBOs. The findings revealed that PBOs prioritize growth, outpacing SBOs but compromising profitability and returns. SBOs, however, while growing at a slower rate, produced superior EBITDA margin expansion and return KPIs, signifying the trade-off between growth and profitability. Efficiency and leverage measures offered no clear distinctions, although SBOs displayed a trend of higher leverage. Nonetheless, the OLS-regression failed to provide statistically significant results, rendering these observations inconclusive. As a result, despite apparent similarities in performance, it remains uncertain whether SBOs deliver inferior or superior operating performance than PBOs. This inherent ambiguity underscores the differing strategic focus depending on the buyout type.

The second research question presented various hypotheses related to drivers, aligned with the VCPs identified in the private equity toolbox and extant literature, which could potentially affect the operating performance of SBOs. Contrarian to conventional expectations, the hypothesis related to pressure investing indicated a strong positive correlation with ROIC and ROE. This implies that SBOs acquired under investment pressure unexpectedly perform better in these return measures. The distribution of pressure investing SBOs was noted to align favorably with equity markets, which might shed light on the contrarian results of the pressure investing hypothesis. Nonetheless, the remaining metrics did not manifest significant results, indicating a more intricate

relationship.

The hypothesis positing that specialized funds outperform generalist funds in terms of operational metrics appears to hold substantial merit. Across almost all categories, specialized funds demonstrate superior performance, revealing a clear trend. While growth rates are comparable between specialized and generalist funds, the profitability of specialized funds is markedly higher, making a significant difference. Furthermore, return and efficiency measures are also higher for specialized funds, with the only exception being lower leverage metrics. The consistency of these results across various metrics suggests that the specific knowledge possessed by specialized funds can be leveraged to create exceptional value.

The academic consensus typically asserts that a swift CEO replacement can positively influence operational value creation. However, the findings of this thesis challenge this notion. There appears to be no substantial evidence suggesting that a CEO change from one year prior to a buyout until two years post-buyout improves operating performance. This particular timeframe may potentially counteract the anticipated positive effects of a CEO change on operating performance. Despite these observations, a distinct trend materialized: the induction of a new CEO typically results in an increased leverage, as reflected in the NIBD/EBITDA ratio, an inference supported by marginal statistical significance

Regarding the other hypotheses about potential determinants driving abnormal operating value creation, the findings were less conclusive. Depending on the metrics assessed, the outcomes pointed in various directions, making any firm conclusions elusive. This complexity necessitates further research for a more comprehensive understanding of these dynamics.

Circling back to the title of the thesis: *Private Equity Trash or Treasure?* The evidence gathered from the meticulously hand-collected financial statement data suggests that it is neither. It seems that SBOs fall somewhere in the middle, reflecting neither extreme. Based on the collected data, there appears to be a variance in operational focus depending on the type of buyout. The underlying data further suggests that financial metrics are more stable in SBOs. This stability in SBOs might imply that there are potentially larger winners and losers in PBOs, whereas SBOs could be a more consistent component in a private equity portfolio.

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Appendices

Appendix A: AIC Models for RQ1

Table A.1: AIC Model Sales Growth

Variables	Step 1	Step 2	Step 3	Step 4	Step 5	Step fit
EBITDA Margin	•	•				
Ln(Assets)	•	✓				
LBO Spread	•	•				
Capital Structure	•	•				
Quick Ratio	•	•				
NWC/Sales	•	•				
AIC Score	-126.8	-129.5				-129.5

✓ denotes that a control variable is added to the model
• signifies that the corresponding control variable is not included in the model
✗ denotes that the control variable is excluded from the model

Table A.2: AIC Model EBITDA

Variables	Step 1	Step 2	Step 3	Step 4	Step 5	Model fit
EBITDA Margin	✓	✓	✗			
Ln(Assets)	•	✓	✓			
LBO Spread	•	•	•			
Capital Structure	•	•	✓			
Quick Ratio	•	•	•			
NWC/Sales	•	•	•			
AIC Score	-532.9	-547.9	-556.7			-556.7

✓ denotes that a control variable is added to the model
• signifies that the corresponding control variable is not included in the model
✗ denotes that the control variable is excluded from the model

Table A.3: AIC Model ROIC

Variables	Step 1	Step 2	Step 3	Step 4	Step 5	Model fit
EBITDA Margin	✓	✗	✓	✗	✓	
Ln(Assets)	•	•	•	•	•	
LBO Spread	•	•	•	•	•	
Capital Structure	•	✓	✓	✓	✓	
Quick Ratio	•	•	•	✓	✓	
NWC/Sales	•	•	•	•	•	
AIC Score	686.7	428.5	426.3	411.9	401.3	401.3

✓ denotes that a control variable is added to the model
• signifies that the corresponding control variable is not included in the model
✗ denotes that the control variable is excluded from the model

Table A.4: AIC Model ROE

Variables	Step 1	Step 2	Step 3	Step 4	Step 5	Model fit
EBITDA Margin	✓	✗	✓	✓	✓	
Ln(Assets)	•	✓	✓	✗	✓	
LBO Spread	•	•	•	✓	✓	
Capital Structure	•	•	•	•	•	
Quick Ratio	•	•	•	•	✓	
NWC/Sales	•	•	•	•	•	
AIC Score	385.4	375.7	367.3	361.1	360.7	360.7

✓ denotes that a control variable is added to the model
• signifies that the corresponding control variable is not included in the model
✗ denotes that the control variable is excluded from the model

Table A.5: AIC Model ROA

Variables	Step 1	Step 2	Step 3	Step 4	Step 5	Model fit
EBITDA Margin	✓	✓	✗	✓	✓	
Ln(Assets)	•	✓	✓	✓	✓	
LBO Spread	•	•	•	•	✓	
Capital Structure	•	•	•	•	•	
Quick Ratio	•	•	✓	✓	✓	
NWC/Sales	•	•	•	•	•	
AIC Score	-295.7	-318.4	-341.7	-343.6	-343.7	-343.7

✓ denotes that a control variable is added to the model
• signifies that the corresponding control variable is not included in the model
✗ denotes that the control variable is excluded from the model

Table A.6: AIC Model Sales/IC

Variables	Step 1	Step 2	Step 3	Step 4	Step 5	Model fit
EBITDA Margin	•	✓	✗	✓		
Ln(Assets)	•	•	•	•		
LBO Spread	•	•	•	•		
Capital Structure	✓	✓	✓	✓		
Quick Ratio	•	•	✓	✓		
NWC/Sales	•	•	•	•		
AIC Score	1642.8	1640.1	1628.8	1626.3		1626.3

✓ denotes that a control variable is added to the model
• signifies that the corresponding control variable is not included in the model
✗ denotes that the control variable is excluded from the model

Table A.7: AIC Model FCF/IC

Variables	Step 1	Step 2	Step 3	Step 4	Step 5	Model fit
EBITDA Margin	•	•	✓			
Ln(Assets)	•	•	•			
LBO Spread	•	•	•			
Capital Structure	•	✓	•			
Quick Ratio	•	•	✓			
NWC/Sales	•	•	•			
AIC Score	108.9	77.9	76.2			76.2

✓ denotes that a control variable is added to the model
• signifies that the corresponding control variable is not included in the model
✗ denotes that the control variable is excluded from the model

Table A.8: AIC Model NIBD/EBITDA

Variables	Step 1	Step 2	Step 3	Step 4	Step 5	Model fit
EBITDA Margin	•					
Ln(Assets)	•					
LBO Spread	•					
Capital Structure	•					
Quick Ratio	•					
NWC/Sales	•					
AIC Score	1494.5					1494.5

✓ denotes that a control variable is added to the model
• signifies that the corresponding control variable is not included in the model
✗ denotes that the control variable is excluded from the model

Table A.9: AIC Model NIBD/FA

Variables	Step 1	Step 2	Step 3	Step 4	Step 5	Model fit
EBITDA Margin	✓	✓	✗	•		
Ln(Assets)	•	✓	✓	✓		
LBO Spread	•	•	•	•		
Capital Structure	•	•	✓	✓		
Quick Ratio	•	•	•	✓		
NWC/Sales	•	•	•	•		
AIC Score	1342.2	1322.4	1309.7	1302.8		1302.8

✓ denotes that a control variable is added to the model
• signifies that the corresponding control variable is not included in the model
✗ denotes that the control variable is excluded from the model

Appendix B: AIC Models for the Fund Specialization Hypothesis in RQ2

Table B.1: AIC Model Sales Growth

Variables	Step 1	Step 2	Step 3	Step 4	Step 5	Model fit
EBITDA Margin	✓	✗	•	•		
Ln(Assets)	•	•	•	•		
LBO Spread	•	✓	✗	•		
Capital Structure	•	•	•	•		
Quick Ratio	•	•	✓	✗		
NWC/Sales	•	•	•	✓		
AIC Score	-140.7	-140.8	-141.3	-141.3		-141.3

✓ denotes that a control variable is added to the model
• signifies that the corresponding control variable is not included in the model
✗ denotes that the control variable is excluded from the model

Table B.2: AIC Model ABITDARegression analysis on EBITDA ME

Variables	Step 1	Step 2	Step 3	Step 4	Step 5	Model fit
EBITDA Margin	✓	✗	✓			
Ln(Assets)	•	✓	✓			
LBO Spread	•	•	•			
Capital Structure	•	•	•			
Quick Ratio	•	•	•			
NWC/Sales	•	•	•			
AIC Score	-246.9	-256.5	-257.5			-257.5

✓ denotes that a control variable is added to the model
• signifies that the corresponding control variable is not included in the model
✗ denotes that the control variable is excluded from the model

Table B.3: AIC Model ROIC

Variables	Step 1	Step 2	Step 3	Step 4	Step 5	Model fit
EBITDA Margin	✓	✗	•	•		
Ln(Assets)	•	✓	✗	✓		
LBO Spread	•	•	•	•		
Capital Structure	•	•	✓	✓		
Quick Ratio	•	•	•	•		
NWC/Sales	•	•	•	•		
AIC Score	53.5	36.5	30.4	20.5		20.5

✓ denotes that a control variable is added to the model
• signifies that the corresponding control variable is not included in the model
✗ denotes that the control variable is excluded from the model

Table B.4: AIC Model ROE

Variables	Step 1	Step 2	Step 3	Step 4	Step 5	Model fit
EBITDA Margin	✓	✓	✓			
Ln(Assets)	•	✓	✓			
LBO Spread	•	•	•			
Capital Structure	•	•	•			
Quick Ratio	•	•	✓			
NWC/Sales	•	•	•			
AIC Score	132.1	121.6	120.5			120.5

✓ denotes that a control variable is added to the model
• signifies that the corresponding control variable is not included in the model
✗ denotes that the control variable is excluded from the model

Table B.5: AIC Model ROA

Variables	Step 1	Step 2	Step 3	Step 4	Step 5	Model fit
EBITDA Margin	✓	✗	•			
Ln(Assets)	•	✓	✓			
LBO Spread	•	•	•			
Capital Structure	•	•	✓			
Quick Ratio	•	•	•			
NWC/Sales	•	•	•			
AIC Score	-164.9	-181.8	-190.1			-190.1

✓ denotes that a control variable is added to the model
• signifies that the corresponding control variable is not included in the model
✗ denotes that the control variable is excluded from the model

Table B.6: AIC Model Sales/IC

Variables	Step 1	Step 2	Step 3	Step 4	Step 5	Model fit
EBITDA Margin	✓	✗	•	•	•	
Ln(Assets)	•	✓	✗	•	•	
LBO Spread	•	•	•	•	•	
Capital Structure	•	•	✓	•	•	
Quick Ratio	•	•	•	•	•	
NWC/Sales	•	•	•	•	•	
AIC Score	546.5	543.3	538.1			538.1

✓ denotes that a control variable is added to the model
• signifies that the corresponding control variable is not included in the model
✗ denotes that the control variable is excluded from the model

Table B.7: AIC Model FCF/IC

Variables	Step 1	Step 2	Step 3	Step 4	Step 5	Model fit
EBITDA Margin	✓	✗	•	•	✓	
Ln(Assets)	•	✓	✗	•	•	
LBO Spread	•	•	✓	✓	✓	
Capital Structure	•	•	•	✓	✓	
Quick Ratio	•	•	•	✓	✓	
NWC/Sales	•	•	•	•	•	
AIC Score	-18.8	-19.9	-30.0	-30.6	-32.9	-32.9

✓ denotes that a control variable is added to the model
• signifies that the corresponding control variable is not included in the model
✗ denotes that the control variable is excluded from the model

Table B.8: AIC Model NIBD/EBITDA

Variables	Step 1	Step 2	Step 3	Step 4	Step 5	Model fit
EBITDA Margin	✓	✗	•	•	•	
Ln(Assets)	•	✓	✗	•	•	
LBO Spread	•	•	✓	•	•	
Capital Structure	•	•	•	•	•	
Quick Ratio	•	•	•	•	•	
NWC/Sales	•	•	•	•	•	
AIC Score	569.3	568.9	568.2			568.2

✓ denotes that a control variable is added to the model
• signifies that the corresponding control variable is not included in the model
✗ denotes that the control variable is excluded from the model

Table B.9: AIC Model NIBD/FA

Variables	Step 1	Step 2	Step 3	Step 4	Step 5	Model fit
EBITDA Margin	✓	✗	•	•	•	
Ln(Assets)	•	✓	✗	•	•	
LBO Spread	•	•	•	•	•	
Capital Structure	•	•	✓	•	•	
Quick Ratio	•	•	•	•	•	
NWC/Sales	•	•	•	•	•	
AIC Score	183.6	180.9	145.9			145.9

✓ denotes that a control variable is added to the model
• signifies that the corresponding control variable is not included in the model
✗ denotes that the control variable is excluded from the model

Appendix C: AIC Algorithm

```
# Excel sheet with only SBO data
sbo_kpis = pd.read_excel('/Users/gustav/Desktop/RQ1 fittingmodel data.xlsx')

# Replace the "SBO" with 1, and everything else with 0
sbo_kpis['Dummy'] = sbo_kpis['Dummy'].apply(lambda x: 1 if x == "SBO" else 0)

control_var = ['EME-1', 'LN(A)', 'LBO S', 'CS', 'QR-1', 'NWC/S-1'] # Removed 'Dummy'

# Create a list of the target columns
target_columns = ['Revenue_CAGR', 'EBITDA ME', 'ROIC ME', 'ROE ME', 'ROA ME',
                  'FCFIC ME', 'NIBD EBITDA ME', 'NIBD Fixed ME', 'REV IC ME']

# DataFrame to hold the results
results_df = pd.DataFrame(columns=['Target', 'AIC', 'Variables'])

for target in target_columns:
    best_aic = None
    best_model = None
    best_combination = []

    # Generate all possible combinations of predictors
    for length in range(len(control_var)+1): # '+1' is necessary to consider all control_var
        for subset in itertools.combinations(control_var, length):
            # 'Dummy' is always included in the subset
            variables = ['Dummy'] + list(subset)
            temp_df = sbo_kpis[variables + [target]].dropna()  # drop rows with NA values

            X = temp_df[variables]
            y = temp_df[target]
            X = sm.add_constant(X)  # Add constant (intercept term)

            model = sm.OLS(y, X)
            results = model.fit()

            if best_aic is None or results.aic < best_aic:
                best_aic = results.aic
                best_model = results
                best_combination = variables

                # Record the current state of the model in the results DataFrame
                results_df = results_df.append({
                    'Target': target,
                    'AIC': best_aic,
                    'Variables': best_combination}, ignore_index=True)

    print(f"Best model for target {target} uses variables {best_combination} with AIC = {best_aic}")

# Show the results DataFrame
print(results_df)
```

[15]

```
# Excel sheet with only SBO data
sbo_kpis = pd.read_excel('/Users/gustav/Desktop/RQ2 fittingmodel data.xlsx')

# One-hot encode the categorical variables
sbo_kpis = pd.get_dummies(sbo_kpis, columns=['Lead partner', 'Fund Size'])

# Group the forced control variables
forced_controls_groups = [
    [col for col in sbo_kpis.columns if 'Lead partner' in col],
    [col for col in sbo_kpis.columns if 'Fund Size' in col]
]

# DataFrame to hold the results
results_df = pd.DataFrame(columns=['Target', 'AIC', 'Variables'])

# Rest of control variables
rest_controls = ['EME-1', 'LN(A)', 'LBO S', 'CS', 'EM-1', 'PM-1', 'QR-1', 'NWC/S-1']

# Target columns
target_columns = ['Revenue_CAGR', 'EBITDA ME', 'ROIC ME', 'ROE ME', 'ROA ME',
                  'FCFIC ME', 'NIBD EBITDA ME', 'NIBD Fixed ME', 'REV IC ME']

for forced_controls in forced_controls_groups:
    for target in target_columns:
        best_aic = None
        best_model = None
        best_combination = []

        # Generate all possible combinations of predictors
        for length in range(1, len(rest_controls) + 1):  # '+1' is necessary to consider all rest_controls
            for subset in itertools.combinations(rest_controls, length):
                # Current forced control is always included in the subset
                variables = list(subset) + forced_controls
                temp_df = sbo_kpis[variables + [target]].dropna()  # drop rows with NA values

                X = temp_df[variables]
                y = temp_df[target]
                X = sm.add_constant(X)  # Add constant (intercept term)

                model = sm.OLS(y, X)
                results = model.fit()

                if best_aic is None or results.aic < best_aic:
                    best_aic = results.aic
                    best_model = results
                    best_combination = variables

                    # Record the current state of the model in the results DataFrame
                    results_df = results_df.append({
                        'Target': target,
                        'AIC': best_aic,
                        'Variables': best_combination}, ignore_index=True)

        print(f"Best model for target {target} with forced controls {forced_controls} uses variables {best_combination} with AIC = {best_aic}")

# Show the results DataFrame
print(results_df)
```

Appendix D: Code for Winsorization

```
# Load all sheets into a dictionary
peers = pd.read_excel("/Users/gustav/Desktop/Filled final data/FF10 new filled.xlsx", sheet_name=[0,1,2,3,4,5,6,7,8,9], skiprows=2)

# Define the names for each DataFrame
names = ["peersff1", "peersff2", "peersff3", "peersff4", "peersff5", "peersff6", "peersff7", "peersff8", "peersff9", "peersff10"]

# Initialize a new dictionary to hold the winsorized data
peers_data = {}

# Loop over each dataframe in the dictionary
for key, name in zip(peers.keys(), names):
    # Fill NA with mean
    df = peers[key].dropna()

    # Separate string and numeric data
    string_data = df.select_dtypes(include=['object'])  # Select string columns
    numeric_data = df.select_dtypes(include=[np.number])  # Select numeric columns

    # Apply winsorizing to each numeric column
    winsorized_data = numeric_data.apply(lambda x: winsorize(x, limits=[0.05, 0.05]), axis=0)

    # Concatenate string labels and winsorized numeric data back together
    df_winsorized = pd.concat([string_data, winsorized_data], axis=1)

    # Assign the winsorized DataFrame to your defined name in peers_data
    peers_data[name] = df_winsorized

for sheet in peers:
    peers[sheet] = peers[sheet]
peersff1 = peers[0]
peersff2 = peers[1]
peersff3 = peers[2]
peersff4 = peers[3]
peersff5 = peers[4]
peersff6 = peers[5]
peersff7 = peers[6]
peersff8 = peers[7]
peersff9 = peers[8]
peersff10 = peers[9]

peers_data = {
    "peersff1": peersff1,
    "peersff2": peersff2,
    "peersff3": peersff3,
    "peersff4": peersff4,
    "peersff5": peersff5,
    "peersff6": peersff6,
    "peersff7": peersff7,
    "peersff8": peersff8,
    "peersff9": peersff9,
    "peersff10": peersff10
}
3]
```

```
    """
    Functions that calculates the margin expansions, based on the what df you want and what year.
    """

    #change year: float to int if writing the value yourself

    def ebitda_me(df: pd.DataFrame, year: float) -> pd.Series:
        # Convert the year to an integer and construct the column names
        year = int(year)
        col_before = f"EBITDA-margin {year - 1}"
        col_after = f"EBITDA-margin {year + 2}"

        # Ensure the columns exist in the dataframe
        if col_before not in df.columns or col_after not in df.columns:
            raise ValueError(f"Data for years {year - 1} or {year + 2} not available in the dataframe.")

        # Calculate the EBITDA margin expansion and return it
        return df[col_after] - df[col_before]


        # Calculate the EBITDA margin expansion and return it
        return df[col_after] - df[col_before]

    def rev_cagr(df: pd.DataFrame, year: float) -> pd.Series:
        year = int(year)
        col_before = f"Revenue {year -1}"
        col_after =f"Revenue {year + 2}"
        if col_before not in df.columns or col_after not in df.columns:
            raise ValueError(f"Data for years {year -1} or {year + 2} not available in dataframe")

        return (df[col_after] / df[col_before]) ** (1/3) - 1

    def roic_me(df: pd.DataFrame, year: float) -> pd.Series:
        year = int(year)
        col_before = f"ROIC {year -1}"
        col_after =f"ROIC {year + 2}"
        if col_before not in df.columns or col_after not in df.columns:
            raise ValueError(f"Data for years {year -1} or {year + 2} not available in dataframe")

        return df[col_after] - df[col_before]



def sbo_vs_peer_rev_cagr(sbo_data: pd.DataFrame, peers_data: dict) -> list:
    results = []

    for index, row in sbo_data.iterrows():
        # Check if "FF10" value is NaN, if it is, add a NaN value to results and continue to next iteration
        if pd.isna(row["FF10"]):
            results.append(np.nan)
            continue

        peer_number = int(round(row["FF10"]))  # round to nearest integer
        peer_df = peers_data.get(f"peersff{peer_number}")

        if peer_df is not None:
            try:
                transaction_year = row["Transaction year"]
                revenue_cagr = rev_cagr(peer_df, transaction_year)
                median_revenue_cagr = revenue_cagr.median()
                margin_expansion = row["Revenue CAGR Period"] - median_revenue_cagr
                results.append(margin_expansion)
            except (ValueError, KeyError):
                results.append(np.nan)  # Append NaN in case of errors
        else:
            results.append(np.nan)  # Append NaN when there's no dataframe for the peer number

    return results
```

Appendix E: Code Snippet for Regression Models

```
## Create individual dataframes

SBO_Revenue_CAGR_df = pd.DataFrame({'SBO_Revenue_CAGR': sbo_vs_peer_rev_cagr(sbo_data, peers_data)})
PBO_Revenue_CAGR_df = pd.DataFrame({'PBO_Revenue_CAGR': pbo_vs_peer_rev_cagr(pbo_data, peers_data)})
SBO_ROIC_ME_df = pd.DataFrame({'SBO_ROIC_ME': sbo_vs_peer_roic_me(sbo_data, peers_data)})
PBO_ROIC_ME_df = pd.DataFrame({'PBO_ROIC_ME': pbo_vs_peer_roic_me(pbo_data, peers_data)})
SBO_EBITDA_ME_df = pd.DataFrame({'SBO_EBITDA_ME': sbo_vs_peer_ebitda_me(sbo_data, peers_data)})
PBO_EBITDA_ME_df = pd.DataFrame({'PBO_EBITDA_ME': pbo_vs_peer_ebitda_me(pbo_data, peers_data)})
SBO_ROE_ME_df = pd.DataFrame({'SBO_ROE_ME': sbo_vs_peer_roe_me(sbo_data, peers_data)})
PBO_ROE_ME_df = pd.DataFrame({'PBO_ROE_ME': pbo_vs_peer_roe_me(pbo_data, peers_data)})
SBO_ROA_ME_df = pd.DataFrame({'SBO_ROA_ME': sbo_vs_peer_roa_me(sbo_data, peers_data)})
PBO_ROA_ME_df = pd.DataFrame({'PBO_ROA_ME': pbo_vs_peer_roa_me(pbo_data, peers_data)})
SBO_FCFIC_ME_df = pd.DataFrame({'SBO_FCFIC_ME': sbo_vs_peer_fcfic_me(sbo_data, peers_data)})
PBO_FCFIC_ME_df = pd.DataFrame({'PBO_FCFIC_ME': pbo_vs_peer_fcfic_me(pbo_data, peers_data)})
SBO_NIBD_EBITDA_ME_df = pd.DataFrame({'SBO_NIBD_EBITDA_ME': sbo_vs_peer_nibd_ebitda_me(sbo_data, peers_data)})
PBO_NIBD_EBITDA_ME_df = pd.DataFrame({'PBO_NIBD_EBITDA_ME': pbo_vs_peer_nibd_ebitda_me(pbo_data, peers_data)})
SBO_NIBD_FIXED_ME_df = pd.DataFrame({'SBO_NIBD_FIXED_ME': sbo_vs_peer_nibd_fixed_me(sbo_data, peers_data)})
PBO_NIBD_FIXED_ME_df = pd.DataFrame({'PBO_NIBD_FIXED_ME': pbo_vs_peer_nibd_fixed_me(pbo_data, peers_data)})
SBO_REV_IC_ME_df = pd.DataFrame({'SBO_Rev_IC_ME': sbo_vs_peer_rev_ic_me(sbo_data, peers_data)})
PBO_REV_IC_ME_df = pd.DataFrame({'PBO_Rev_IC_ME': pbo_vs_peer_rev_ic_me(pbo_data, peers_data)})

# Combine dataframes
aops_df = pd.concat([SBO_Revenue_CAGR_df, PBO_Revenue_CAGR_df, SBO_ROIC_ME_df, PBO_ROIC_ME_df, SBO_EBITDA_ME_df,
                     PBO_EBITDA_ME_df, SBO_ROE_ME_df, PBO_ROE_ME_df, SBO_ROA_ME_df, PBO_ROA_ME_df,
                     SBO_FCFIC_ME_df, PBO_FCFIC_ME_df, SBO_NIBD_EBITDA_ME_df, PBO_NIBD_EBITDA_ME_df, SBO_NIBD_FIXED_ME_df, PBO_NIBD_FIXED_ME_df, SBO_REV_IC_ME_df, PBO_REV_IC_ME_df], axis=1)

# Write DataFrame to an excel
#df.to_excel("output.xlsx")
aops_df.to_excel("/Users/gustav/Desktop/AOP with rev_ic .xlsx")
```

```
# Define your independent (explanatory) variables
X = nibdfixed[['sbo', 'LN(A)', 'CS', 'QR-1']]

# Add a constant (intercept term) to the independent variables
X = sm.add_constant(X)

# Define your dependent (response) variable
y = nibdfixed['NIBD Fixed ME']

# Fit the model
model = sm.OLS(y, X)
results = model.fit()
robust_results = results.get_robustcov_results(cov_type='HC3')

# Print out the statistics
print(robust_results.summary())


##Prediction
pred_nibdfixed = robust_results.predict(X)

# Compute differences between actual and predicted values
diff = y - pred_nibdfixed

# Perform the Wilcoxon signed-rank test
w, p = stats.wilcoxon(diff)

# Print the result
print('The Wilcoxon signed-rank test statistic value is: {}'.format(w))
print('The p-value for the Wilcoxon signed-rank test is: {}'.format(p))
```

```python
def run_regression(df, target_col, determinant, control_vars):
    control_var = df.loc[:, control_vars]  # changed this line
    # Add the additional column
    X = control_var.copy()
    X[determinant] = df[determinant]

    # This is the dependent variable
    y = df[target_col]

    # Concatenate X and y for dropping NaN values
    data = pd.concat([X, y], axis=1)

    # Drop rows with any NaN values in X or y
    data = data.dropna()

    # Split up X and y again
    X = data[X.columns]
    y = data[y.name]

    # Add a constant to the independent value
    X = sm.add_constant(X)

    # Fit the model
    model = sm.OLS(y, X)
    results = model.fit()
    robust_results = results.get_robustcov_results(cov_type='HC3')

    # Prediction
    pred = robust_results.predict(X)

    # Compute differences between actual and predicted values
    diff = y - pred

    # Perform the Wilcoxon signed-rank test
    w, p = stats.wilcoxon(diff)

    # Print the results
    print(robust_results.summary())
    print('The Wilcoxon signed-rank test statistic value is: {}'.format(w))
    print('The p-value for the Wilcoxon signed-rank test is: {}'.format(p))

    # Return the results object for further manipulation
    return robust_results
```

CEO replacement

[21]

```
# Define your list of control variable sets
control_var_list_ceo = [['QR-1'],
                        ['EME-1', 'LN(A)'],
                        ['EME-1'],
                        ['LN(A)', 'CS',],
                        ['EME-1', 'LN(A)', 'QR-1'],
                        ['LN(A)', 'CS'],
                        ['EME-1', 'LBO S', 'CS', 'QR-1'],
                        ['LBO S'],
                        ['CS']]

# Create a list to store the output widgets
output_widgets = [widgets.Output() for _ in range(len(target_columns))]

# Create a 3x3 grid to display the widgets
grid = widgets.GridBox(output_widgets, layout=widgets.Layout(grid_template_columns="repeat(3, 1fr)"))
display(grid)

# Run the regression function on each target column
for i, target_col in enumerate(target_columns):
    with output_widgets[i]:
        run_regression(sbo_kpis, target_col, 'CEO', control_var_list_ceo[i])
```

Appendix F: Examples of Regression Output in RQ1

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          NIBD Fixed ME   R-squared:                       0.229
Model:                            OLS   Adj. R-squared:                  0.216
Method:                 Least Squares   F-statistic:                     8.857
Date:                Tue, 04 Jul 2023   Prob (F-statistic):           1.07e-06
Time:                        14:20:24   Log-Likelihood:                -646.42
No. Observations:                 250   AIC:                             1303.
Df Residuals:                     245   BIC:                             1320.
Df Model:                           4
Covariance Type:                  HC3
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          2.7135      0.823      3.298      0.001       1.093       4.334
sbo           -0.8422      0.268     -3.145      0.002      -1.370      -0.315
LN(A)         -0.6926      0.193     -3.589      0.000      -1.073      -0.313
CS            -0.5598      0.347     -1.614      0.108      -1.243       0.123
QR-1           0.9233      0.416      2.220      0.027       0.104       1.743
==============================================================================
Omnibus:                      135.234   Durbin-Watson:                   2.184
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              689.590
Skew:                           2.223   Prob(JB):                    1.81e-150
Kurtosis:                       9.815   Cond. No.                         14.6
==============================================================================
...
Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)
The Wilcoxon signed-rank test statistic value is: 11849.0
The p-value for the Wilcoxon signed-rank test is: 0.0007970043976406658
```

Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...

```
                            OLS Regression Results
==============================================================================
Dep. Variable:           Revenue_CAGR   R-squared:                       0.047
Model:                            OLS   Adj. R-squared:                  0.039
Method:                 Least Squares   F-statistic:                     5.664
Date:                Tue, 04 Jul 2023   Prob (F-statistic):            0.00393
Time:                        14:20:24   Log-Likelihood:                 67.745
No. Observations:                 250   AIC:                            -129.5
Df Residuals:                     247   BIC:                            -118.9
Df Model:                           2
Covariance Type:                  HC3
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.1678      0.037      4.553      0.000       0.095       0.240
sbo           -0.0378      0.024     -1.552      0.122      -0.086       0.010
LN(A)         -0.0211      0.011     -1.948      0.053      -0.042       0.000
==============================================================================
Omnibus:                       70.812   Durbin-Watson:                   1.997
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              150.846
Skew:                           1.384   Prob(JB):                     1.75e-33
Kurtosis:                       5.611   Cond. No.                         9.73
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)
The Wilcoxon signed-rank test statistic value is: 13228.0
The p-value for the Wilcoxon signed-rank test is: 0.031638203254005494
```

Appendix G: Examples of Regression Output in RQ2

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               EBITDA ME   R-squared:                       0.129
Model:                            OLS   Adj. R-squared:                  0.102
Method:                 Least Squares   F-statistic:                     4.745
Date:                Wed, 12 Jul 2023   Prob (F-statistic):            0.00392
Time:                        13:41:12   Log-Likelihood:                 130.10
No. Observations:                 102   AIC:                            -252.2
Df Residuals:                      98   BIC:                            -241.7
Df Model:                           3
Covariance Type:                  HC3
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0679      0.026     -2.631      0.010      -0.119      -0.017
EME-1         -0.1017      0.086     -1.176      0.242      -0.273       0.070
LN(A)          0.0193      0.006      3.496      0.001       0.008       0.030
CEO           -0.0096      0.018     -0.547      0.586      -0.045       0.025
==============================================================================
Omnibus:                       13.888   Durbin-Watson:                   2.635
Prob(Omnibus):                  0.001   Jarque-Bera (JB):               27.678
Skew:                           0.489   Prob(JB):                     9.77e-07
Kurtosis:                       5.357   Cond. No.                         40.0
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)
The Wilcoxon signed-rank test statistic value is: 2558.0
The p-value for the Wilcoxon signed-rank test is: 0.819128944760254
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  ROA ME   R-squared:                       0.200
Model:                            OLS   Adj. R-squared:                  0.158
Method:                 Least Squares   F-statistic:                     4.888
Date:                Wed, 12 Jul 2023   Prob (F-statistic):           0.000500
Time:                        13:41:12   Log-Likelihood:                 95.125
No. Observations:                 102   AIC:                            -178.3
Df Residuals:                      96   BIC:                            -162.5
Df Model:                           5
Covariance Type:                  HC3
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.1592      0.051     -3.095      0.003      -0.261      -0.057
EME-1          0.2613      0.204      1.283      0.202      -0.143       0.665
LN(A)          0.0325      0.008      3.985      0.000       0.016       0.049
EM-1          -0.4743      0.246     -1.931      0.056      -0.962       0.013
QR-1          -0.0041      0.018     -0.224      0.823      -0.041       0.032
CEO           -0.0134      0.019     -0.711      0.479      -0.051       0.024
==============================================================================
Omnibus:                        1.515   Durbin-Watson:                   2.270
Prob(Omnibus):                  0.469   Jarque-Bera (JB):                1.022
Skew:                           0.015   Prob(JB):                        0.600
Kurtosis:                       3.489   Cond. No.                         158.
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)
The Wilcoxon signed-rank test statistic value is: 2611.0
The p-value for the Wilcoxon signed-rank test is: 0.9587344153094637
```

OLS Regression Results

Dep. Variable:	NIBD EBITDA ME	R-squared:	0.067
Model:	OLS	Adj. R-squared:	-0.002
Method:	Least Squares	F-statistic:	1.407
Date:	Wed, 12 Jul 2023	Prob (F-statistic):	0.211
Time:	15:08:37	Log-Likelihood:	-281.23
No. Observations:	103	AIC:	578.5
Df Residuals:	95	BIC:	599.5
Df Model:	7		
Covariance Type:	HC3		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.5110	168.174	0.003	0.998	-333.357	334.379
LN(A)	0.5847	0.330	1.773	0.079	-0.070	1.239
LBO S	-119.7441	63.967	-1.872	0.064	-246.734	7.246
CS	-1.7360	1.013	-1.714	0.090	-3.747	0.275
Lead partner_0.0	3.6773	168.169	0.022	0.983	-330.181	337.535
Lead partner_1.0	3.4583	168.170	0.021	0.984	-330.401	337.318
Lead partner_2.0	3.8226	168.170	0.023	0.982	-330.038	337.683
Lead partner_3.0	3.1243	168.170	0.019	0.985	-330.735	336.984

Omnibus:	2.420	Durbin-Watson:	2.108
Prob(Omnibus):	0.298	Jarque-Bera (JB):	2.146
Skew:	-0.042	Prob(JB):	0.342
Kurtosis:	3.702	Cond. No.	761.

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)
The Wilcoxon signed-rank test statistic value is: 2618.0
The p-value for the Wilcoxon signed-rank test is: 0.8435183465111855

OLS Regression Results

Dep. Variable:	EBITDA ME	R-squared:	0.173
Model:	OLS	Adj. R-squared:	0.147
Method:	Least Squares	F-statistic:	7.271
Date:	Wed, 12 Jul 2023	Prob (F-statistic):	0.000187
Time:	13:43:36	Log-Likelihood:	132.75
No. Observations:	102	AIC:	-257.5
Df Residuals:	98	BIC:	-247.0
Df Model:	3		
Covariance Type:	HC3		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0789	0.024	-3.233	0.002	-0.127	-0.030
EME-1	-0.1056	0.086	-1.229	0.222	-0.276	0.065
LN(A)	0.0194	0.005	3.694	0.000	0.009	0.030
Spec	0.0392	0.014	2.779	0.007	0.011	0.067

Omnibus:	17.097	Durbin-Watson:	2.520
Prob(Omnibus):	0.000	Jarque-Bera (JB):	38.591
Skew:	0.577	Prob(JB):	4.17e-09
Kurtosis:	5.783	Cond. No.	39.9

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)
The Wilcoxon signed-rank test statistic value is: 2605.0
The p-value for the Wilcoxon signed-rank test is: 0.942784223659666

OLS Regression Results

Dep. Variable:	Revenue_CAGR	R-squared:	0.007
Model:	OLS	Adj. R-squared:	-0.013
Method:	Least Squares	F-statistic:	0.2547
Date:	Wed, 12 Jul 2023	Prob (F-statistic):	0.776
Time:	13:43:36	Log-Likelihood:	73.659
No. Observations:	102	AIC:	-141.3
Df Residuals:	99	BIC:	-133.4
Df Model:	2		
Covariance Type:	HC3		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.0455	0.016	2.790	0.006	0.013	0.078
NWC/S-1	0.0474	0.072	0.662	0.509	-0.095	0.190
Spec	-0.0036	0.025	-0.142	0.887	-0.053	0.046

Omnibus:	1.094	Durbin-Watson:	2.433
Prob(Omnibus):	0.579	Jarque-Bera (JB):	1.166
Skew:	0.180	Prob(JB):	0.558
Kurtosis:	2.620	Cond. No.	5.35

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)
The Wilcoxon signed-rank test statistic value is: 2497.0
The p-value for the Wilcoxon signed-rank test is: 0.6655273476098453

OLS Regression Results

Dep. Variable:	NIBD EBITDA ME	R-squared:	0.063
Model:	OLS	Adj. R-squared:	0.025
Method:	Least Squares	F-statistic:	2.504
Date:	Wed, 12 Jul 2023	Prob (F-statistic):	0.0472
Time:	13:46:12	Log-Likelihood:	-278.91
No. Observations:	102	AIC:	567.8
Df Residuals:	97	BIC:	581.0
Df Model:	4		
Covariance Type:	HC3		

	coef	std err	t	P>|t|	[0.025	0.975]
const	4.2873	1.986	2.158	0.033	0.345	8.230
LN(A)	0.6056	0.310	1.955	0.053	-0.009	1.220
LBO S	-121.8861	57.800	-2.109	0.038	-236.603	-7.169
CS	-1.7304	0.979	-1.768	0.080	-3.673	0.212
Spec 3+	-0.5554	0.748	-0.742	0.460	-2.041	0.930

Omnibus:	2.272	Durbin-Watson:	2.128
Prob(Omnibus):	0.321	Jarque-Bera (JB):	1.935
Skew:	-0.043	Prob(JB):	0.380
Kurtosis:	3.669	Cond. No.	744.

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)
The Wilcoxon signed-rank test statistic value is: 2549.0
The p-value for the Wilcoxon signed-rank test is: 0.7958597026097632

Appendix H: Overview of FF10 Industry Classifications

1. Consumer Nondurables: Food, Tobacco, Textiles, Apparel, Leather, Toys
    - 0100-0999
    - 2000-2399
    - 2700-2749
    - 2770-2799
    - 3100-3199
    - 3940-3989
2. Consumer Durables: Cars, TVs, Furniture, Household Appliances
    - 2500-2519
    - 2590-2599
    - 3630-3659
    - 3710-3711
    - 3714-3714
    - 3716-3716
    - 3750-3751
    - 3792-3792
    - 3900-3939
    - 3990-3999
3. Manufacturing: Machinery, Trucks, Planes, Chemicals, Office Furniture, Paper, Commercial Printing
    - 2520-2589
    - 2600-2699
    - 2750-2769
    - 2800-2829
    - 2840-2899
    - 3000-3099
    - 3200-3569
    - 3580-3621
    - 3623-3629
    - 3700-3709
    - 3712-3713
    - 3715-3715
    - 3717-3749

- 3752-3791
- 3793-3799
- 3860-3899

4. Energy: Oil, Gas, and Coal Extraction and Products
    - 1200-1399
    - 2900-2999
5. Information Technology: Business Equipment: Computers, Software, and Electronic Equipment
    - 3570-3579
    - 3622-3622
    - 3660-3692
    - 3694-3699
    - 3810-3839
    - 7370-7372
    - 7373-7373
    - 7374-7374
    - 7375-7375
    - 7376-7376
    - 7377-7377
    - 7378-7378
    - 7379-7379
    - 7391-7391
    - 8730-8734
6. Telecommunications: Telephone and Television Transmission
    - 4800-4899
7. Retail: Wholesale, Retail, and Some Services (Laundries, Repair Shops)
    - 5000-5999
    - 7200-7299
    - 7600-7699
8. Healthcare: Healthcare, Medical Equipment, and Drugs
    - 2830-2839
    - 3693-3693
    - 3840-3859
    - 8000-8099
9. Utilities

- 4900-4949

10. Other: Mines, Construction, Construction materials, Transportation, Hotels, Bus Service, Entertainment, Finance

Appendix I: Complete List of SBO Transactions

Company	Country	Transaction Year	FF10 Industry	Fund vehicle	Fund size (mEUR)
ABAX AS	NO	2017	5	Investcorp Technology Partners IV	354
AddSecure AB	SE	2016	5	ABRY Heritage Partners	477
Ahlsell AB	SE	2006	7	Cinven IV	6.500
AIBEL AS	NO	2007	4	Herkules Private Equity Fund II	376
Akademikliniken HJ AB	SE	2016	8	Polaris IV	448
Almondy Holding AB	SE	2008	1	Segulah III	224
Anläggning & Kabel Entreprenad i Malmö AB	SE	2017	10	Triton Fund IV	3.556
Anticimex AB	SE	2012	10	EQT VI	4.750
Aptilo Networks AB	SE	2011	5	Norvestor V	236
Asolvi AS	NO	2019	5	Volpi Capital Fund I	185
ATOS Medical AB	SE	2011	8	EQT VI	4.750
Aura Group AB	SE	2006	10	FSN Capital II	151
Basefarm AS	NO	2012	5	ABRY VII	1.150
Bladt Industries A/S	DK	2012	3	Nordic Capital Fund VII	4.300
Bramming Plast-Industri A/S	DK	2016	3	Blue Equity II	95
Bravida AB	SE	2012	10	Bain Capital Europe III	3.500
Broadcast Text International AB	SE	2013	10	Carlyle Europe Technology Partners II	530
BTX Group A/S	DK	2013	7	Sun Capital Partners VI	1.582
Cambio Healthcare Systems AB	SE	2012	5	Valedo Partners Fund II	217
Car-O-Liner Group AB	SE	2012	2	Polaris III	365
Cint AB	SE	2016	5	Nordic Capital Fund VIII	3.591
Color Print A/S	DK	2006	1	Polaris II	270
Com Hem AB	SE	2006	6	Carlyle Europe Partners II	1.800
Com Hem AB	SE	2011	6	BC European Cap IX	6.687
Conscia A/S	DK	2015	5	Axcel IV	485
Covidence A/S	DK	2019	5	EMK Capital Partners	811
CREM International Holding AB	SE	2012	2	Priveq Investment Fund IV	196
Duett AS	NO	2015	5	Procuritas Capital Investors V	204
Duett AS	NO	2019	5	Accel-KKR Growth Capital Partners IV	1.350
EET A/S	DK	2015	1	FSN Capital IV	465
EG A/S	DK	2013	5	Axcel IV	485
Egain International AB	SE	2016	10	Summa Equity I	465
El-Björn AB	SE	2016	3	Connecting Capital	321
Ellepot A/S	DK	2013	3	Capidea Kapital II	97
Envidan A/S	DK	2020	10	Waterland Private Equity Fund VI	1.279
Envirotainer AB	SE	2018	3	Cinven VI	7.000
Envirotainer AB	SE	2010	3	AAC Capital NEBO Fund II	955
ETON Group AB	SE	2016	1	EQT VII	6.817
Etraveli Group AB	SE	2010	10	Segulah IV	572
Eurowrap A/S	DK	2007	1	LD Equity II	456
Faerch Plast Group A/S	DK	2017	3	Advent Global Private Equity VIII	11.712
Fiskarhedenvillan Group AB	SE	2012	10	Litorina IV	286
Flokk AS	NO	2014	3	Triton Fund IV	3.556
GET AS	NO	2007	6	Quadrangle Capital Partners II	1.513
Gotessons Industri AB	SE	2019	3	Accent Equity VI	313
Handicare AS	NO	2005	8	Herkules Private Equity Fund I	240
Hansen Ärotection AS	NO	2013	1	IK VII Fund	1.356
Happy Socks AB	SE	2017	1	Palamon European Equity II	402
Helly Hansen AS	NO	2006	1	Altor Fund II	1.150
Huscompagniet A/S	DK	2011	10	FSN Capital III	380
Inflight Service Intressenter AB	SE	2010	7	TRITON II	1.126

Continued on the next page

Company	Country	Transaction Year	FF10 Industry	Fund vehicle	Fund size (mEUR)
Intrum AB	NO	2014	10	Nordic Capital Fund VIII	3.591
IT Relation A/S	DK	2018	5	Genesis 8	2.200
JKF Industri A/S	DK	2012	3	LD Equity III	95
Jotul AS	NO	2018	3	OpenGate Capital Fund I	265
KMD Equity Holding A/S	DK	2012	7	Advent Global Private Equity VII	8.500
Kongsberg Automotive ASA	NO	2001	1	FSN Capital I	54
KP Components A/S	DK	2014	3	Segulah IV	572
Lekolar AB	SE	2007	7	3i Eurofund V	5.000
LGT Logistics AB	SE	2015	10	Litorina Kapital Fund IV	278
Logent AB	SE	2013	10	Adelis Equity Partners Fund I	759
Logstor A/S	DK	2013	3	Triton Fund III	2.383
Louis Poulsen A/S	DK	2019	2	Investindustrial Fund VI	2.035
Nille AS	NO	2011	7	BC European Cap IX	6.687
Nordic Paper AS	NO	2014	3	Special Situations Venture Partners II	342
Norstat Norge AS	NO	2019	5	Triton Smaller Mid-Cap Fund I	448
Optimizely AB	SE	2010	5	IK 2007 Fund	1.675
Optimizely AB	SE	2014	5	Accel-KKR Capital Partners IV	585
Optiware A/S	DK	2013	5	Capidea Kapital II	97
Oral Care AB	SE	2017	8	Accent Equity Fund V	437
Penetrace AS	NO	2018	5	Verdane Capital IX	291
Permobil AB	SE	2013	8	Investor AB	68
Persson Innovation AB	SE	2018	3	Ceder Capital II	94
Phadia AB	SE	2007	5	Cinven IV	6.500
Piab Group Holding AB	SE	2016	3	EQT VII	6.817
Plastal Group AB	SE	2005	1	Nordic Capital Fund V	1.500
Puzzel AS	NO	2019	5	Marlin Equity Partners V	2.025
Qleanair Scandinavia AB	SE	2012	10	Priveq Investment IV	198
Q-Matic Holding AB	SE	2007	5	Altor Fund II	1.150
Ryds Bilglas AB	SE	2018	10	Nordic Capital Fund VIII	3.591
S:T Eriks AB	SE	2015	3	Accent Equity Fund V	437
San Sac AB	SE	2014	10	Accent Equity Fund V	437
SEM AB	SE	2016	3	Procuritas Capital Investors V	204
Sortera Group AB	SE	2016	10	Summa Equity I	465
SSG A/S	DK	2012	10	BWB Partners II	134
STENI Holding AS	NO	2013	3	Accent Equity V	427
Stormgeo Holding AS	NO	2014	5	EQT Mid Market	1.600
Tampnet AS	NO	2012	6	EQT Infrastructure II	1.938
TCM Group A/S	DK	2016	10	IK Small Cap I Fund	277
The North Alliance AS	NO	2018	10	Norvestor VII	570
THULE Group AB	SE	2014	2	Accent Equity II	680
TIA Technology A/S	DK	2014	5	EQT Mid-Market Fund I	1.100
Troax AB	SE	2013	3	FSN Capital III	380
Twister Cleaning Technology AB/ HTC Group AB	SE	2013	3	Polaris III	365
Unifaun AB/ Nshift AB	SE	2016	5	Vitruvian Investment Partnership II	1.220
Unifeeder A/S	DK	2013	10	Nordic Capital Fund VIII	3.591
Unisport Scandinavia AB	SE	2015	10	Vaaka Partners Buyout II	150
Visolit AS	NO	2016	5	IK VII Fund	1.356
VSM Group AB	SE	2006	3	Kohlberg Investors V	645
Welltec A/S	DK	2007	4	Summit Partners Private Equity Fund	2.340
Yrkesakademin AB	SE	2014	10	CapMan Buyout X	244
Zizzi Denmark ApS	DK	2019	1	Findos Investor	230
Ålö Aktiebolag AB	SE	2011	3	Altor Fund III	2.000

Appendix J: Complete List of PBO Transactions

Company	Country	Transaction Year	FF10 Industry	Acquirer
ABAX AS	NO	2012	5	Norvestor Equity AS
Academedia AB	SE	2010	5	EQT V
AddPro AB	SE	2017	5	Adelis Equity Partners AB
Aditro Logistics AB	SE	2012	10	Valedo Partners
Admincontrol As	NO	2015	5	Herkules Capital AS
Advantec AS	NO	2010	3	Norvestor V, L.P.
Airlift AS	NO	2006	10	Reiten & Co
Akademikliniken AB	SE	2011	8	Valedo Partners
Ammeraal Beltech Modular A/S	DK	2015	3	Advent International Corporation
Apsis International AB	SE	2010	5	Norvestor Equity AS
AutoStore AS	NO	2017	10	EQT Partners AB
Avonova Helse AS	NO	2011	8	Herkules Private Equity Fund III
Bambora Device AB	SE	2014	10	Cidron SuperPay AB
Barnmorskegruppen Mama Mia AB	SE	2018	8	Nordstjernan AB
Baum und Pferdgarten A/S	DK	2020	2	Verdane
Bellakvarter A/S	DK	2012	10	SolstraCapital Partners A/S
Bennex AS	NO	2006	4	CET Holding AS
Biomega AS	NO	2017	1	AMERRA Capital Management, LLC
Bramming Plast-Industri A/S	DK	2007	3	LD Invest Equity
Broadridge Trading and Connectivity Solutions AB	SE	2012	5	Orc Group Holding AB
Budweg Caliper A/S	DK	2018	2	Capidea Management ApS
Bygardsservice AS	NO	2019	10	Valedo Partners
Byredo AB	SE	2013	1	ManzanitaCapital UK LLP
Cabonline Group AB	SE	2015	10	H.I.G. Europe Realty Partners
Caldic Ingredients Denmark AS	DK	2011	1	Maj Invest Equity A/S
Capio AB	SE	2006	8	Opica AB
CarpetVista AB	SE	2015	2	Litorina Capital Advisors AB
Cibes Lift AB	SE	2017	3	Nalka Invest AB
Conexus AS	NO	2019	5	Verdane
Con-Form AS	NO	2012	3	Reiten & Co Capital Partners VII
Cutters AS	NO	2019	10	Procuritas AB
Dako Danmark AS	DK	2007	8	EQT Partners AB
Delmar Systems AS	NO	2013	10	HitecVision AS
Det Danske Madhus A/S	DK	2014	10	PolarisManagement A/S
Digpro AB	SE	2017	5	Litorina Capital Advisors AB
Eco Log Sweden AB	SE	2017	3	Accent Equity Partners AB
EcoOnline AS	NO	2014	5	Viking Venture AS
Ecura Bo og Habilitering AS	NO	2016	8	Longship AS
Ellab A/S	DK	2016	8	IK Investment Partners
Eson Pac Group AB	SE	2015	3	Inter IKEA Investments AB
Etac Ab	SE	2007	8	Nordstjernan AB
Eterni Norge AS	NO	2017	10	Herkules Capital AS
eTRAVELi Group AB	SE	2017	10	CVC Capital Partners Limited
Eurowrap A/S	DK	2007	3	LD Invest Equity
Exotic Snacks AB	SE	2008	1	Segulah Advisor AB
Exsitec AB	SE	2017	5	Standout Capital
Faerch A/S	DK	2014	3	EQT Partners AB
Fitness World A/S	DK	2015	10	FSN Capital Partners AS

Continued on the next page

Company	Country	Transaction Year	FF10 Industry	Acquirer
Foxway AB	SE	2019	5	Norvestor Equity AS
Fractal Gaming AB	SE	2016	5	Litorina Capital Advisors AB
Frontit AB	SE	2018	5	Priveq Investment
Frosunda Omsorg AB	SE	2007	8	Polaris Management A/S
Future Production AS	NO	2013	4	Norvestor VI, L.P.
Geia Foods A/S	DK	2017	1	Credo Partners AS
Gummigrossen i Örnsköldsvik AB	SE	2019	2	Altor Equity Partners AB
Hantverksdata Sverige AB	SE	2018	5	Adelis Equity Partners AB
HB-Care A/S	DK	2014	10	CataCap Management Aps
Heavycast Karlstad AB	SE	2008	3	Primaca Partners Oy
Hector Rail AB	SE	2014	10	EQT Partners AB
Helgstrand Dressage ApS	DK	2018	2	Waterland Private Equity Investments
Hermes Medical Solutions AB	SE	2016	8	Segulah Advisor AB
Holmris B8 A/S	DK	2017	3	BWB Partners P/S
Hypergene AB	SE	2016	5	Monterro 2
InFiber AS	NO	2011	6	EQT VI
Isadora AB	SE	2018	1	Axcel Management A/S
It-Total Sweden Ab	SE	2019	5	Segulah Advisor AB
Iver VÄSt Ab	SE	2018	5	EQT Partners AB
Jernforsen Energi System AB	SE	2011	3	Alder Fund I
Jetpak Group AB	SE	2005	10	Polaris Management A/S
Jobandtalent People Sweden AB	SE	2016	10	Varenne AB
JOBmeal AB	SE	2016	1	BDT Capital Partners
Jupiter Bach A/S	DK	2016	3	Verdane Capital VIII K/S
Kabal AS	NO	2019	5	Norvestor Equity AS
Karsten Moholt AS	NO	2018	3	HitecVision AS
Kemetyl AB	SE	2007	3	Segulah Advisor AB
King Oscar AS	NO	2010	1	Procuritas Capital Investors VI Holding
Klimatror AB	SE	2014	3	FSN Capital Partners AS
KungSängen Produktion AB	SE	2015	2	Litorina Capital Advisors AB
Lakrids By Johan Bülow A/S	DK	2016	1	Valedo Partners
LingIT AS	NO	2017	5	Verdane
Lyngsoe Systems A/S	DK	2014	5	Catacap Management A/S
MacroBond Financial AB	SE	2018	5	Nordic Capital
Marine Aluminium AS	NO	2012	3	Norvestor Equity AS
Maritech AS	NO	2017	5	Broodstock Capital
Menigo AB	SE	2006	1	Nordic Capital
Menu A/S	DK	2019	2	Polaris Management A/S
Mersalg AS	NO	2018	10	Preato Capital AB
Midsona AB	SE	2016	8	Priveq Investment
Mountain Top Industries A/S	DK	2017	2	Axcel Management A/S
MW Security AB	SE	2012	3	Century International Co., Ltd
NeTel AB	SE	2013	6	Axcel Management A/S
NETS A/S	DK	2018	10	Advent International Corporation
NGI A/S	DK	2014	3	Adelis Equity Partners AB
Nordentic AB	SE	2017	8	Adelis Equity Partners AB
Norsk Jernbanedrift AS	NO	2011	3	Herkules Private Equity Fund III
Norwegian Fishfarming Technologies AS	NO	2018	3	Longship AS

Continued on the next page

Company	Country	Transaction Year	FF10 Industry	Acquirer
Novia Sverige AB	SE	2010	10	BWB Partners
NOX Consulting AB	SE	2019	10	Broviken Gruppen AB
Nutid AB	SE	2019	5	Small Cap Partners
One Nordic AB	SE	2011	10	Altor Fund III Limited
Outpost24 AB	SE	2016	5	Monterro 2
Persson Innovation AB	SE	2012	3	Connecting Capital
Perten Instruments AB	SE	2010	5	Valedo Partners
Petroleum Technology Company AS	NO	2013	4	Herkules Capital AS
Pharmaq AS	NO	2013	8	Permira Advisers Ltd.
PicaDeli AB	SE	2012	1	Fidelio Capital
PM Retail AS	NO	2012	2	FSN Capital Partners AS
Powerbox International AB	SE	2013	5	Alder Fund I
Premier Is - Mejerigaarden AS	DK	2008	1	Erhvervsinvest Management A/S
Presserv AS	NO	2016	3	Norvestor Equity AS
Progressive A/S	DK	2011	5	Greystone Capital A/S
Prototal AB	SE	2019	3	Nalka Invest AB
Rapid Images AB	SE	2015	5	Arctos Equity Partner
Real Time Solutions AB	SE	2018	5	ShortCap AB
REKOM Group A/S	DK	2018	2	CataCap Management Aps
Robust AB	SE	2013	10	Norvestor Equity AS
Safran Software Solutions AS	NO	2013	5	Progressus Management AS
Sales Support Sweden AB	SE	2015	10	SSNG Holding AB
SBC Sveriges Bostadsrattscentrum AB	SE	2019	10	Fidelio Capital AB
SCANCOIN AB	SE	2010	5	Segulah Advisor AB
Scanmarket A/S	DK	2019	5	Verdane
Secunia ApS	DK	2013	5	DKA Capital A/S
Skånska Byggvaror AB	SE	2012	2	Polaris Management A/S
Speed Group AB	SE	2015	10	Ratos AB
Sperre Air Power AS	NO	2018	3	Norvestor Equity AS
Staur Fjellbakeri AS	NO	2013	1	Staur Private Equity AS
Stofa A/S	DK	2010	6	Ratos AB
Svend Hoyer A/S	DK	2016	3	Solix Group AB
Svensk Markservice AB	SE	2010	10	Inter IKEA Investments AB
Systemsikring AS	NO	2017	3	Longship AS
Tacton Systems AB	SE	2017	5	Kirk Kapital A/S
Tampnet AS	NO	2010	6	HitecVision AS
Tawi AB	SE	2016	3	SEB Venture Capital
Temperature Sensitive Solutions Systems Sweden AB	SE	2011	5	Investor Group
Therma Industri AS	NO	2019	3	Broodstock Capital
Tommy Nordbergh Åkeri AB	SE	2016	10	Accent Equity Partners AB
TRINTECH AS	NO	2007	5	Via Venture Partners A/S
Trivec Systems AB	SE	2015	5	Sequent Invest AB
TrueSec AB	SE	2018	5	Sobro AB
Unident AB	SE	2018	8	Triton Partners
Vega Sea A/S	DK	2012	1	Maj Invest Equity A/S
Ventelo AS	SE	2012	6	EQT Partners AB
View Ledger AB	NO	2019	10	Explore Equity Partners
VisBook AS	NO	2019	5	Standout Capital
Westpack A/S	DK	2017	3	Capidea Management ApS
ÅKers AB	SE	2008	3	Altor Equity Partners AB
Aarbakke AS	NO	2006	4	HitecVision AS

Appendix K: Complete List of Comparison Group

Company	Country	FF10 Industry	Company	Country	FF10 Industry
Bakkafrost P/F	NO	1	NKT A/S	DK	2
Carlsberg A/S	DK	1	Scandinavian Brake systems A/S	DK	2
Scandinavian Tobacco Group	DK	1	Svedbergs i Dalstorp AB	SE	2
Cloetta AB	SE	1	Autoliv AB	SE	2
Ellen AB	SE	1	Gullberg & Jansson AB	SE	2
Firstfarms A/S	DK	1	Pandora A/S	DK	2
Harboes Bryggeri A/S	DK	1	Absolent Air Care Group AB	SE	3
MOWI ASA	NO	1	AKVA group ASA	NO	3
Orkla ASA	NO	1	Rockwool A/S	DK	3
Royal Unibrew A/S	DK	1	AQ Group AB	SE	3
Skåne-möllan AB	SE	1	Arcoma AB	SE	3
Elanders AB	SE	1	BE Group AB	SE	3
Eniro Group AB	SE	1	Beijer Alma AB	SE	3
Gabriel Holding A/S	DK	1	Borregaard ASA	NO	3
Grieg Seafood ASA	NO	1	Bdr. Klee A/S	DK	3
Gyldendal A/S	DK	1	Brødrene Hartmann A/S	DK	3
Ege Carpets A/S	DK	1	Bulten AB	SE	3
Mackmyra AB	SE	1	Clemondo Group AB	SE	3
MQ Holding AB	SE	1	Concentric	SE	3
NHST Holding AS	NO	1	CTT Systems AB	SE	3
North Media A/S	DK	1	F.E. Bording A/S	DK	3
RNB Retail and Brands AB	SE	1	Flügger A/S	DK	3
Salmar ASA	NO	1	Glunz & Jensen Holding A/S	DK	3
Axfood AB	SE	1	Goodtech ASA	NO	3
Bergman & Beving AB	SE	1	Gunnebo AB	SE	3
Børdreme A & O Johansen A/S	DK	1	H+H International A/S	DK	3
Clas Ohlson AB	SE	1	Hexagon Composites ASA	NO	3
Electra Gruppen AB	SE	1	ITAB Shop Concept AB	SE	3
Matas A/S	DK	1	Lindab International AB	SE	3
Lyko Group AB	SE	1	MultiQ International AB	SE	3
New Wave Group AB	SE	1	Nolato AB	SE	3
Sportamore AB	SE	1	Obducat AB	SE	3
Swedol AB	SE	1	Profilgruppen AB	SE	3
Rizzo Group AB	SE	1	Rottneros AB	SE	3
Andersen & Martini Holding A/S	DK	2	SKAKO A/S	DK	3
Bang & Olufsen A/S	DK	2	Tomra Systems ASA	NO	3
Ekornes ASA	NO	2	Nekkar ASA	NO	3
Lego A/S	DK	2	VBG Group AB	SE	3
GN Store Nord A/S	DK	2	Equinor ASA	NO	4
Byggmax Group AB	SE	2	Akastor ASA	NO	4
Boconcept	DK	2	Aker BP ASA	NO	4
AB Electrolux	SE	2	DNO ASA	NO	4
Fagerhult AB	SE	2	Dome Energy AB	SE	4
FM Mattson Mora Group AB	SE	2	Electromagnetic Geoservices ASA	NO	4
Haldex AB	SE	2	Dolphin Drilling AS	NO	4
KABE group AB	SE	2	Orrön Energy AB	SE	4
Lamhults Design Group AB	SE	2	PGS ASA	NO	4
Meko AB	SE	2	Spectrum ASA	NO	4
Midway Holding AB	SE	2	Roblon A/S	DK	5

Company	Country	FF10 Industry	Company	Country	FF10 Industry
Exalt AB	SE	5	Scatec ASA	NO	9
Columbus A/S	DK	5	5th Planet Games A/S	DK	10
Bouvet ASA	NO	5	A.P. Møller - Mærsk A/S	DK	10
Addnode Group AB	SE	5	AB Volvo	SE	10
cBrain A/S	DK	5	Absolent Air Care Group AB	SE	10
Firefly AB	SE	5	AF Gruppen ASA	NO	10
SimCorp A/S	DK	5	AIK Fotboll AB	SE	10
Asetek A/S	DK	5	Alleima AB	SE	10
Atea ASA	NO	5	Alm. Brand A/S	DK	10
Binero Group AB	SE	5	AMSC ASA	NO	10
Netcompany A/S	DK	5	ASSA ABLOY AB	SE	10
Crayon Group Holding ASA	NO	5	Auriant Mining AB	SE	10
Nordic Semiconductor ASA	NO	5	Belships ASA	NO	10
Hexagon AB	SE	5	Cadeler A/S	DK	10
Moment Group AB	SE	6	Dampskibsselskabet Norden A/S	DK	10
North Media A/S	DK	6	DFDS A/S	DK	10
Telenor ASA	NO	6	DSV A/S	DK	10
Telia Company AB	SE	6	Eltel AB	SE	10
Polaris Media ASA	NO	6	Eolus Vind AB	SE	10
Telefonaktiebolaget LM Ericsson	SE	6	FM Mattsson Mora Group AB	SE	10
Tele2 AB	SE	6	Scandic Hotels Group AB	SE	10
Millicom International Cellular S.A.	NO	6	Rockwool A/S	DK	10
Modern Times Group MTG AB	SE	6	Topdanmark A/S	DK	10
Net Insight AB	SE	6	Tryg A/S	DK	10
Allgon AB	SE	6	Norwegian Air Shuttle ASA	NO	10
NextGenTel Holding ASA	NO	6	Norsk Hydro ASA	NO	10
Jobindex A/S	DK	6			
Mediaprovider Scandinavia AB	SE	6			
Ambu A/S	DK	8			
Bactiguard Holding AB	SE	8			
Bavarian Nordic A/S	DK	8			
BioGaia AB	SE	8			
BioInvent International AB	SE	8			
Boule Diagnostics AB	SE	8			
C-Rad AB	SE	8			
Dedicare AB	SE	8			
Elekta AB	SE	8			
MedCap AB	SE	8			
Medistim ASA	NO	8			
Medivir AB	SE	8			
Midsona AB	SE	8			
Orexo AB	SE	8			
Photocure ASA	NO	8			
Vitrolife AB	SE	8			
Novo Nordisk A/S	DK	8			
Arise AB	SE	9			
EAM Solar ASA	NO	9			
Elmera Group ASA	NO	9			
Orrön Energy AB	SE	9			
Ørsted A/S	DK	9			