Norwegian School of Economics
Bergen, Fall 2018

Beyond the Usual Suspects: Impact of Private Equity on Industries and Competitors of Portfolio Companies

Evidence from the Norwegian Market

Rasmus Mollan Høgmo & Thomas Sebu

Supervisor: Carsten Bienz

Master's Thesis in MSc of Finance

NORWEGIAN SCHOOL OF ECONOMICS

Abstract*

Although much evidence supports that private equity enhances performance for the companies backed by it, many critics claim it destroys value. Numerous concerns also relate to its impact on the economy. Based on this, we go beyond the usual suspects, being portfolio companies, and examine the impact of private equity on industries and the close competitors of portfolio companies. Using a novel dataset of Norwegian buyouts supplied by the Argentum Centre for Private Equity, combined with a dataset on Norwegian corporate accounts compiled by the Centre for Applied Research at NHH, we document this impact. We find that industries experiencing buyout activity outperform industries that do not experience buyout activity. Moreover, findings suggest industries with comparatively high buyout activity outperform industries with lower levels of buyout activity, but the effect disappears when employing detailed industry classifications. This supports the notion of spillover effects. Finally, we find no spillovers to individual competitors, providing evidence that the spillovers are industry wide. Overall, these findings are consistent with the hypothesis that private equity backed companies force industry peers to improve and indicate the effect be industry wide.

*We are grateful to Prof. Dr. rer. pol. Carsten Bienz for his insight and guidance throughout the writing process and for initially suggesting the topic of this thesis. This allowed us to explore a topic widely unknown to ourselves and many others alike, providing a valuable learning opportunity.

Contents

1. INTRODUCTION 1

2. PRIVATE EQUITY 5

2.1 INTRODUCTORY ABOUT PRIVATE EQUITY 5

2.2 THE NORWEGIAN PRIVATE EQUITY MARKET 7

3. RELATED LITERATURE ON PRIVATE EQUITY 10

4. HYPOTHESES 14

5. DATA 15

5.1 SAMPLE SELECTION 15

5.2 SAMPLE DESCRIPTION 17

5.3 PROPENSITY SCORE MATCHING 20

6. METHODOLOGY 23

6.1 A NOTE ON TREATMENT EFFECTS AND CAUSALITY 23

6.2 RESEARCH QUESTION ONE 24

6.3 RESEARCH QUESTION TWO 27

7. EMPIRICAL RESULTS 29

7.1 IMPACT OF BUYOUTS ON INDUSTRY PERFORMANCE 29

7.1.1 Total Output 29

7.1.2 Value Added 31

7.1.3 Fixed Capital Growth 32

7.1.4 Growth in Number of Companies 33

7.1.5 Further Discussion 35

7.2 IMPACT OF BUYOUTS ON COMPETITORS OF PORTFOLIO COMPANIES 36

7.2.1 Operational Performance 37

7.2.2 Financial Performance 39

7.2.3 Distress Risk *41*

7.2.4 Further Discussion *41*

8. LIMITATIONS **43**

9. CONCLUSION AND IMPLICATIONS FOR FURTHER RESEARCH **44**

10. REFERENCES **46**

11. APPENDICES **51**

11.1 APPENDIX A – DESCRIPTION OF VARIABLES 51

11.2 APPENDIX B – OUTPUT OF ADDITIONAL ANALYSES 53

List of Tables

1	Buyout Transactions by Industry…………………………………………………………	19
2	Impact of Buyout Activity on Total Industry Output……………………………………..	30
3	Impact of Buyout Activity on Industry Value Added…………………………………….	31
4	Impact of Buyout Activity on Industry Fixed Capital Growth……………………………	33
5	Impact of Buyout Activity on Number of Companies per Industry………………………	34
6	Impact of Buyout Activity on Competitors' Operational Performance…………………..	38
7	Impact of Buyout Activity on Competitors' Financial Performance……………………..	39
8	Impact of Buyout Activity on Competitors' Distress Risk……………………………….	40
A1	Variable Descriptions……………………………………………………………….	51
B1-B11	Output of Additional Analyses…………………………..……………………………	53

List of Figures

1	Total PE investment in Norwegian Companies by Year in million NOK…………………	8
2	Total number of PE investments in Norwegian Companies by Year…………………….	8

1. Introduction

Private equity (PE) ownership in companies has spurred confusion and uncompromising opinions. For instance, in the last few years, private equity involvement has been given much blame for the so-called retail apocalypse, referring to the rapid disappearance of stores in the retail industry. Such stories tend to stick with people, biasing their views towards the entire asset class being bad news for the economy. Furthermore, Fraser-Sampson (2010, p. 1) argues that private equity is plausibly the most misunderstood asset class there is. Considering that private equity has been riding a wave of growth in recent years, hence increasing in importance for companies, individuals and policymakers alike, this sounds concerning. While it indeed is a somewhat different and, at first sight, complex asset class, we argue that it is in the best of interest to clearly understand its implications for the economy. This thesis adds to the literature that challenges the negative views formed upon the likes of the introductory story, the view being that private equity destroys value, rather than creating it.

Very few papers have researched the implications of private equity activity on industry performance, but the select few that have generally use global data and supply evidence that private equity activity results in higher industry performance (see e.g. (Aldatmaz & Brown, 2018) and (Bernstein, et al., 2017)). Would it be possible to identify the same effect for industry performance in single nations, like Norway? Furthermore, much research supports the notion that private equity backing improves the performance of the companies they back (see e.g. (Kaplan, 1989), (Lerner, et al., 2011) and (Davis, et al., 2014)). This is indeed a favourable outcome, but what happens to competitors of the companies that receive backing? Do they experience any spillovers from private equity activity? These questions embody the pressing concerns this thesis intends to explore.

This thesis contributes to the increasingly extensive private equity research by exploring the impact on less researched aspects, thus going beyond the usual suspect of the portfolio companies. In the work of Bienz (2016a), the impact of private equity backing on the respective industries and competitors of portfolio companies are highlighted as aspects we know little about. Understanding these aspects is of high importance in assessing the overall effect occurring from private equity, especially for e.g. policymakers, due to spillover effects. Adding to this, Aldatmaz and Brown (2018) also point out that the effect of private equity on industry dynamics is widely unexplored.

To the best of our knowledge, most of the research on private equity covers a global scale or the US. This is especially true when considering the specific topics of this thesis. This paper is unique in that it addresses these questions for the Norwegian market. Additionally, little academic research has been conducted in the field for Norway in general and the case of Norway is in itself interesting, considering it is a small and open economy, heavily reliant on oil. On the other hand, this might result in private equity fund managers selecting certain industries in favour of others, which is a typical and pressing issue in private equity research. This thesis adopts the innovative approach of employing multiple levels of industry classifications, ranging from 14 distinctive coarse classifications to 799 distinctive sub-classifications, in order to address and combat the issue at hand. Finally, much of the research focus on somewhat earlier periods. As an example, Bernstein, et al. (2017), which is arguably one of the most prominent papers on the effect of private equity on industries, covers investments to 2009. In contrast, this thesis covers all years from 1992 to 2015, owing to a well-kept dataset. This is highly relevant, since private equity has experienced high growth in later years, and Norway is far from an exception to this growth.

This thesis utilises consolidated- and unconsolidated accounts for all Norwegian companies together with all private equity buyout transactions, and then measures possible spillover effects of said buyout activity on industries and competitors of portfolio companies. More specifically, we tackle the following research questions:

1. How is industry performance impacted by private equity buyout activity?

2. What impact does private equity buyouts have on competitors of the portfolio companies they back?

In the analysis of industry performance, we uncover two main findings. First, industries experiencing buyout activity outperform industries that do not experience buyout activity, in terms of growth in total output, value added, fixed capital and number of companies. These findings are highly robust to increasingly detailed industry classifications and controls, suggesting the effect be due to improvements by private equity funds actively managing the companies in their portfolio. Second, industries experiencing a comparatively high number of buyouts outperform industries experiencing lower number of buyouts. However, the effect disappears when employing the finest industry classification available. Consequently, this suggests that the effect is due to industry *spillovers* and not due to general partners selecting the most promising industries.

Building on the findings for research question one, we hypothesise whether said spillover effects are identifiable in individual companies in industries experiencing buyouts, specifically close competitors of portfolio companies. Overall, the findings suggest that spillover effects from buyout activity is an industry wide effect, rather than being mainly attributable to close competitors of portfolio companies.

In order to address the aforementioned research questions, we begin by constructing a unique dataset that serves as the foundation of this thesis. Investment data on 192 buyouts are retrieved from the Argentum Centre for Private Equity (ACPE) database and merged together with a database of accounting-, industry- and company information for Norwegian companies, compiled by the Centre for Applied Research at NHH (SNF) and NHH. The data cover the period 1992-2015, which accordingly is the basis for the analysis. For the industry analysis, we distinguish industries that have experienced a buyout in the last five years as buyout industries; otherwise, the industry is a non-buyout industry. The five-year period was motivated by the average holding period for our sample being 5.08 years. The resulting aggregate industry-region-year observations are then utilised in panel data OLS regressions incorporating rich controls for fixed industry-, region- and year effects.

In order to obtain a sample of close competitors and a comparable control group, namely distant competitors, we employ a matching procedure known as Propensity Score Matching. First, we restrict the matching to find matches in 1992-2012, since we intend to analyse performance up to three years post buyout. This reduces the original sample of 192 buyouts to 152 buyouts. Following the strict matching procedure, we are left with 96 pairs of distant- and close competitors. Finally, difference-in-differences estimation is applied to the sample.

A pressing issue in much of the literature is dealing with the direction of causality, specifically whether the observed effect is due to private equity itself or superior selection by general partners. This thesis bestows a great deal of attention to this issue and attempts to design the methodology to account for it. First, we employ rich sets of controls for unobserved heterogeneity, increasing the plausibility of isolating the causal effect, while at the same time reducing bias. Second, we hypothesise that it should be practically random which sub-industries are selected for investment. Hence, applying classifications with a multitude of sub-industries should further reduce the selection effect. Third, we apply Propensity Score Matching to produce a sample of close competitors that we hypothesise are affected by private equity spillovers and a counterfactual sample that is not affected. In combination with difference-in-differences estimation, this is thought to capture spillover effects.

As a final remark, we observe that related literature yield results complementary to ours. Aldatmaz and Brown (2018) research- and find spillover effects from private equity investments using a dataset covering 48 countries and 19 industries in 1990-2011, provided by Burgiss. An advantage of their dataset is certainly larger samples, but also the inclusion of invested private equity capital in actual dollars at the industry level. This serves as a good proxy for private equity activity. There are two great advantages to our dataset. First, we have all private firms in the sample, allowing for analysis of the effect on the whole industry. Few others have this opportunity. Second, the dataset has available multiple levels of industry classifications as well as having significantly more categories within the levels. This allows us to more precisely pinpoint where the buyout transactions occur. They also employ a different statistical method, using a panel vector auto regression method (panel-VAR).

This thesis relates in multiple ways to the work of Bernstein, et al. (2017), considering that our methodology for research question one was largely based on their work. They also investigate the effect of private equity investment on industry performance and find mostly positive outperformance by buyout industries. Their dataset spans across 26 OECD countries and 20 industries in the period 1991-2009. Again, we have the advantage of more detailed industry classifications, while they have larger samples. Furthermore, they state that data limitations prevent further examination of spillovers. Fortunately, our dataset might allow for this, thus building on their work.

The thesis is structured as follows. Chapter 2 describes private equity and presents key statistics on the European private equity market, before turning to a more in-depth description of the Norwegian private equity market. Chapter 3 examines related literature, while Chapter 4 introduces hypotheses. Chapter 5 explains the sample selection process and Chapter 6 sets up the methodological approach. Chapter 7 presents the results, followed by notes on potential limitations of said results in chapter 8. Chapter 9 concludes and suggests avenues for further research.

2. Private Equity

2.1 Introductory About Private Equity

In its simplest definition, private equity (PE) is a medium to long-term equity investment into non-publicly traded companies, characterised by active ownership (Invest Europe, n.d.). Fraser-Sampson (2010, chapter 1) argues that while the traditional definitions of private equity hold for the majority of occurrences of the phenomenon, they have proven troublesome for a while. As we will learn in the forthcoming, the multiple types of private equity and its unique characteristics complicate providing a universal definition.

A buyout (BO) or more formally known, leveraged buyout, usually involves a larger portion of outside debt financing in order to acquire mature or declining companies (Kaplan & Strömberg, 2009). In contrast to buyout, venture capital (VC) usually concerns young companies in their introductory stage. Furthermore, Metrick and Yasuda (2010, chapter 11) find that the popular assumption of all equity financing in venture capital is indeed close to the truth. Metrick and Yasuda (2010, chapter 1) also highlight another key difference between venture capital and buyout, namely that venture capital firms usually acquire a minority stake in the companies they purchase, while buyout firms acquire a majority stake. Building on this, they point out that total funds under management for buyout are about three times that of venture capital. To that end, buyouts not surprisingly garner the biggest media headlines.

In recent times, this convenient binary categorisation might not be adequate. Fraser-Sampson (2010) points to growth- and development capital as distinctive to buyout and venture, and that they are frequently mistaken and/or forced into one of these categories. We will briefly discuss these two steadily emerging forms of private equity. Similar to buyout capital, development capital usually concerns mature or declining companies, but is distinguished in two key aspects: development capital usually takes a minority stake in the companies that are purchased and defers from utilising acquisition debt (Fraser-Sampson, 2010). Growth capital can seem very similar to venture, but differs in that it usually targets the stage after venture, but before buyout, namely the growth stage. With time, we assume that this fine line between the four types will be more clearly distinguished. For the purpose of this thesis, the focus is entirely on buyout transactions.

Private equity investments are carried out by private equity funds, which are invariably structured as limited partnerships (Cendrowski, et al., 2012, chapter 2). Investors in private equity funds are typically referred to as limited partners (LPs) and fund managers as general partners (GPs). Banks, insurance companies and corporations were early enthusiasts during the conception of private equity, being later accompanied by such as pension funds, government agencies, university endowments and foundations. In terms of funds raised in Europe in 2017, pension funds were the largest investor in buyouts and government agencies were the largest investor in venture capital, accounting for respectively 37% and 29% of capital raised for each type (Invest Europe, 2018). Throughout its existence, a private equity firm generally manages several funds, each with an average lifetime of 10 years (Cendrowski, et al., 2012, p. 7). Additionally, the separate fund is a collection of individual investments, regarded as target- or portfolio companies. These portfolio companies have traditionally been held and improved upon for an average of 3-5 years (Preqin, 2015) and then divested in order to realise the return. The mode of divestment is typically referred to as an exit strategy, with the most common ones being trade sales (sale to non-financial line organisations), secondary sales (sale to another private equity firm) and initial public offerings (IPO) (Kaplan & Strömberg, 2009). Write-offs also do occur. In Europe in 2017, trade sales accounted for 35%, secondary sales 28% and IPOs 14% (Invest Europe, 2018).

Private equity is a relatively young, alternative asset class, which the comparatively low volume of academic work in the field in the 1980s and 1990s underline (Cumming, 2010). The number of buyout transactions and total value of transactions have steadily grown since 1985, until experiencing a dip in 2000-2001 (Kaplan & Strömberg, 2009). The industry was booming as the global financial crisis approached, with 2006 and 2007 seeing a record amount of funds raised, followed by the inevitable slump in activity. The European private equity market has since then displayed strong growth, reaching €91.9bn in funds raised in 2017, the highest level since 2006 (Invest Europe, 2018). Moreover, 2017 saw European invested capital total €71.7bn and divestment value (at cost) total €42.7bn, a very significant increase from a stagnant 2016.

Buyouts accounted for €51.2bn of the €71.7bn invested capital and €32.6bn of the €42.7bn divested (Invest Europe, 2018). In contrast, venture capital accounted for €6.4bn and €2.1bn in respectively invested- and divested capital. Furthermore, 40% of the buyout market was represented by so-called mega buyouts, which are buyouts greater than €300m. In their annual Private Equity Trend Report, PwC (2018) reports a total of 1,431 buyout deals (investments and exits) taking place in Europe in 2017, a 10.5% increase on a year-to-year basis. At a neat €13.4bn, 2016 experienced the largest European buyout deal ever, but despite this feat, the top 10 deals of 2017 almost surpassed the entirety of buyout deals in 2016 in terms of value.

2.2 The Norwegian Private Equity Market

The establishment of the Norwegian Venture Capital and Private Equity Association (NVCA) in 2001 (Wiese-Hansen & Nordal, 2018), indicates that private equity is still a recent phenomenon in the Norwegian market. Additionally, Invest Europe, formerly known as EVCA, was founded as early as 1983, which adds up to a lifespan twice that of NVCA, illustrating how young the Norwegian private equity market indeed is. Despite its youth, assets under management for members of the NVCA grew from €900m in 2001 to €10bn as of today. Although 2016 was a year of relatively weak growth for private equity due to turbulence in the energy sector, it has since made a strong comeback. Hence, the Norwegian private equity market is, much like the Norwegian market in general, volatile. Before moving on, we note that it is not just the financials of private equity experiencing an increase. Both the number of fund managers and funds have also seen significant growth (Wiese-Hansen & Nordal, 2018).

When it comes to Norwegian legislation, which is important for the establishment, structuring and operation of private equity firms, Norway arguably falls a bit short. As of writing their chapter in "The Private Equity Review", Wiese-Hansen and Nordal (2018) emphasise Norway's lack of tailored private equity legislation when explaining that choice of company structure is limited and issues in attracting target investors are prominent. The result is the majority of the largest and most professional Norwegian private equity firms seeking other jurisdictions to call home. Examples include HitecVision and Norvestor in Guernsey, and FSN Capital and Herkules Capital in Jersey (Argentum, n.d.). On a positive note, the Norwegian government has shown involvement in private equity by establishing venture capital company, Investinor AS, and its buyout counterpart, Argentum (Hammerich & Heistad, 2018). Argentum is also the largest private equity fund in the history of the Nordic region and still heavily government-backed today (Wiese-Hansen & Nordal, 2018).

Information and communications technology (ICT), petroleum and retail dominate the Norwegian private equity firms' portfolios (Syrstad & Grimsby, 2017). This holds true when we look at both value creation and employment in the underlying portfolio companies. Post

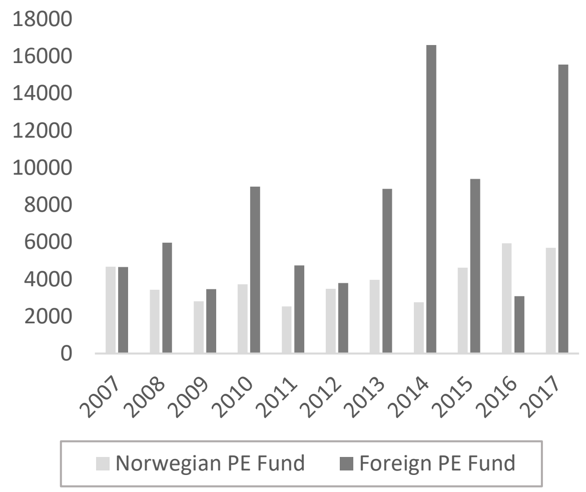

Figure 1. Total PE investment in Norwegian companies by year in million NOK
Source: (Menon Economics, 2018, p.27)

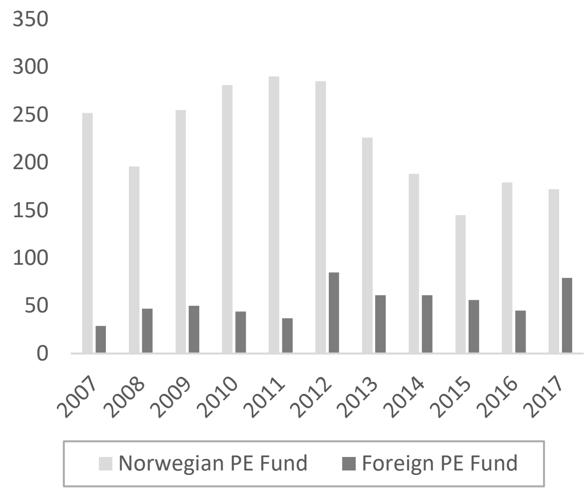

Figure 2. Total number of PE investments in Norwegian companies by year
Source: (Menon Economics, 2018, p.28)

2009, ICT took over the lead from petroleum as the largest sector for private equity investment, in terms of value creation. Furthermore, in their report for NVCA, Menon Economics (2018) points out that the investment trend in IT is still increasing and investments in the petroleum- and life science industries continue to fall. In terms of investments in NOK, Norwegian private equity funds decreased their total investments from almost NOK 12bn in 2016 to NOK 8.5bn in 2017. Furthermore, NOK 21.25bn was invested in *Norwegian* companies by both Norwegian and foreign funds in 2017. Buyouts in IT accounted for NOK 11.16bn of this total, business related services and industry services for NOK 3.26bn, and petroleum for NOK 2.54bn. In terms of number of transactions, IT experienced 15 buyouts, business related services and industry services 7, and petroleum 18. In total, these three industries accounted for roughly 82% of the buyout value in NOK and 62.5% of transactions.

From figure 1 and figure 2, one is able to make various observations. First, as previously noted, the Norwegian private equity market is highly volatile, especially in terms of total investment. Secondly and arguably the most interesting observation, is that foreign funds on average invest far more in terms of NOK, while they make significantly fewer transactions in sheer numbers. This implies on average considerably larger deal sizes for foreign investors and thus a higher proportion of buyout transactions. In 2007, Norwegian funds and foreign funds invested roughly the same amount, with respectively NOK 4.67bn and NOK 4.65bn. In 2017, these numbers grew to respectively NOK 5.69bn and NOK 15.56bn, an enormous increase for foreign funds. Furthermore, Norwegian funds did not surpass their total investment level in 2007 until 2016. Looking at the number of investments, Norwegian funds made 252 separate investments in 2007, while foreign funds made merely 29. This is close to being tenfold. In 2017, Norwegian funds made 172 investments, while foreign made 79. We also find it compelling to comment on the development in NOK invested in relation to major economic events. Both Norwegian and foreign investments fell following the global financial crisis, which is not surprising. There was a major reduction in foreign investments in 2010, when the European debt crisis hit the EU. Finally, foreign investments fell drastically in 2014, when the oil shock hit Norway. Norwegian investments in NOK surprisingly increased. This could suggest that Norwegian GPs had better knowledge and faith in the Norwegian market.

In 2016, the Norwegian private equity-backed portfolio companies employed roughly 68,900 people (Syrstad & Grimsby, 2017). Not surprisingly, buyout transactions, which are usually in large companies, accounted for 84% of the total employment. In 2017, buyout transactions accounted for NOK 20.53bn or 97% of the total NOK 21.25bn invested in Norwegian companies (Menon Economics, 2018). This is a decent increase on a year-to-year basis, considering 2016 saw 91% of NOK invested being buyout. Evidently, an overwhelmingly large share of private equity in NOK in Norway are buyouts. On the other hand, buyout transactions account for 74 or short of one third of the 251 individual transactions. Foreign buyout firms have recently been especially active in the Norwegian market, conducting many large-scale buyouts in 2017, with four deals surpassing NOK 2bn and three deals surpassing NOK 1bn. This explains the massive fivefold increase in foreign investments in Norwegian companies from 2016 to 2017 in figure 1.

The Norwegian pension fund recently and yet again rejected private equity in entirety from their portfolio (Bloomberg, 2018). This is surprising considering the decision went against advice from the fund itself and a government-appointed expert group. Nevertheless, it is an interesting note in light of the substantial implications that would follow if the fund were to include private equity in its portfolio. In this regard, a 5% allocation would imply close to €50bn allocated to private equity (NBIM, n.d.), a stark contrast to the €91.7bn raised in Europe in 2017 (Invest Europe, 2018). However, discussing the investment decisions of the Norwegian pension fund is evidently outside the scope of this thesis.

Looking forward, the future looks bright for the Norwegian private equity market. Wiese-Hansen and Nordal (2018) predict that the Norwegian private equity market will become increasingly international and that a growing number of foreign investors will want to put their money in Norwegian buyouts as well as ventures. Furthermore, the government is already engaged in the private equity industry, through already mentioned Investinor and Argentum, and have strongly signalled significant increases in financial support. This holds especially true for venture capital and incubator projects. Hammerich and Heistad (2018) add that Norwegian private equity funds need to adjust to constantly changing regulatory requirements in the financial sector and that use of mezzanine financing[1], due to more restricted bank lending, is increasingly normal. Additionally, they mention a likely bias towards long-term investments, since authorities propose changes in capital requirements for pension funds.

3. Related Literature on Private Equity

A wealth of academic research supports the central Jensen hypothesis (Jensen, 1989) that private equity backed companies operationally outperform public companies due to better incentives and more efficient management of resources (see e.g. (Kaplan, 1989), (Lerner, et al., 2011), and (Davis, et al., 2014)). In contrast, a relatively scarce amount of academic research exists on whether private equity creates spillovers to overall industry performance and the competitors of portfolio companies. In this chapter, we first briefly explore literature outside the private equity field documenting spillover effects, to support the lack of said papers on private equity. Similar to private equity, such as foreign direct investments may e.g. introduce new technology and managerial expertise to the target company, which spills over to the industry as a whole (Aldatmaz & Brown, 2018). Next, we examine implications of spillovers in private equity literature and finally discuss advantages to this thesis.

In terms of alternative research on spillover effects, Bernstein and Nadiri (1989) find that spillovers from companies' investment in research and development (R&D) lower the overall cost within an industry, due to industry peers absorbing technology and knowledge. Additionally, studies on foreign direct investments have shown that multinational corporations contribute positive spillovers on domestic industries they enter (Blomström & Kokko, 1998). The magnitude of the effect varies between countries and industries, but is believed to be stronger with higher levels of local capabilities and competition. The latter can be illustrated

[1] Mezzanine debt is debt lower in seniority to another debt from the same issuer, but higher than equity (Investopedia, n.d.).

with a paper written by Caves (1974), who finds a higher presence of multinational firms in the Australian manufacturing industry to coincide with increased productivity. In contrast, when exploring Canada, he was unable to uncover this connection. This was arguably due to higher tariffs in Canada restricting increased competition. However, the positive view presented in this paragraph is not unanimous throughout research. Aitken and Harrison (1999) argue, through their sample of 4000 Venezuelan firms, that foreign investments are value destroying for plants not receiving this backing. In other words, negative spillover effects.

One would expect either of the following three outcomes when assessing spillovers from companies backed by private equity to the industry peers. First, the competitive pressure can increase because of private equity investment, forcing the competitors to become more efficient by e.g. adopting new technology. Since competitors improve their operations, positive industry spillovers thus exist. Second, as suggested by the literature, portfolio companies backed by private equity experience performance enhancements. This increase in performance could be at the cost of competitors' performance, with a severe consequence being customers fleeing away from competitors, resulting in industry-wide negative spillovers. Third, there could be no effect at all beyond targeted portfolio companies.

In three consecutive papers, Bernstein, et al. ((2010), (2014), (2017)) focus on whether private equity investments in industries affect aggregate growth rates of productivity, employment and capital formation. Additionally, they address whether said growth rates come at the expense of increased cyclicality. By employing a dataset of private equity investments across 20 industries in 26 OECD countries between 1992 and 2009, they find that industries with presence of private equity grow faster in terms of productivity and employment. They continue by exploring whether one can differentiate between industries with different levels of private equity involvement, but find few significant relationships. This could suggest that spillovers from private equity backed companies to their industry peers exist, but they state that data limitations prevent them from researching this further.

Aldatmaz and Brown (2018) complement the research conducted by Bernstein, et al. (2017). One major difference is they focus on the effect of private equity on aggregate industry measures for *publicly* listed companies, thus leaving the portfolio companies out of the sample. In addition, their dataset contains values of private equity transactions in dollars, functioning as a proxy for private equity activity. Building on this, they attempt to capture spillover effects from portfolio companies to companies within the same industry that do not receive private equity backing. With a sample consisting of 19 industries across 48 countries in 1990-2011 supplied by Burgiss, they find industry-level capital expenditure to grow faster following private equity investments. Additionally, they find profitability-, employment- and labour productivity growth to increase in an industry post private equity investment, consistent with the results by Bernstein, et al. (2017). Moreover, Aldatmaz and Brown find growth to be steepest in competitive industries, suggesting spillovers due to competition. Competitors not backed by private equity react to the efficiency improvements of portfolio companies by becoming increasingly competitive, resulting in an overall industry improvement.

Some papers investigating private equity spillovers in specific industries also exist. One such paper, by Chevalier (1995), examines the effect of leveraged buyouts of supermarket chains on the competitors. She conducts an event study of four supermarket chains and find the market value and expected profits of competitors to increase following the announcement of a leveraged buyout. Furthermore, presence of leveraged buyouts encourages expansion by local competitors already in the same region as the buyout and entry by competitors outside the region. Somewhat similar to Chevalier, Bernstein and Sheen (2016) examine restaurant chain buyouts and document changes in their operational practices. Hypothesising that franchises within the same chain are unaffected by private equity practices due to being legally independent units, franchises are thought to serve as a counterfactual. Building on this, they find support of positive spillover effects from directly owned restaurants to those that are franchised, since franchises of the same geographic location as directly owned restaurants outperform those of a different one.

The increasing attention to private equity's effect on the economy and its research comes to light through more channels than just the sheer volume of academic research. As an illustrative example, in a publication by large, multinational company Ernst & Young (EY) in collaboration with the Institute for Private Capital (Brown & Witte, 2018) the impact of private equity on the economy is assessed. The publication largely rely on much of the work discussed in this chapter, which also highlights the importance of academic work in the field. Although most academic work and publications support the view that private equity confers positive outcomes, contradictions occur. Fonseka, et al. (2018) analyse Chinese companies, mainly listed in China, and find that competitors experience a decrease in stock price, following announcements of private equity placements. The negative competitive spillover effect dominates in the short-term and a contagion effect mostly explain the long-term. However, it is pointed out that stock markets in China function differently to other markets that are major and mature.

Although there being a constant discussion of whether private equity firms cause the improvements for industries or simply superiorly select industries that are more prosperous, Harford, et al. (2015) argue, in line with Aldatmaz and Brown (2018), that the industry improvements are most likely driven by the increased competition private equity creates. They find industry peers to react defensively post a leveraged buyout by e.g. increasing investment in R&D, change governance practices or engage in strategic alliances and/ or acquisitions, rather than copying what the portfolio company is doing. While they are unable to completely rule out the selection motives for leveraged buyouts, they find more support for the competitive effect hypothesis of spillovers. Similarly, examining how competitors' governance is affected following leveraged buyouts in their industry, Oxman and Yildirim (2008) find significant changes in corporate governance. Specifically, they find governance practices at portfolio companies to spill over on their competitors following buyouts.

This thesis complements much of the discussed related literature and is able to overcome some of the weaknesses in said literature. One definite advantage is the availability of all private firms in the sample. This allows for analysis of the industry as a whole and not just for a given portion of the industry, as is the case in previous empirical work. Considering few others have this opportunity, this thesis is an important contribution to the literature. Another major advantage is the opportunity to conduct analyses on multiple levels of industry classifications. There are available classifications with respectively 14, 87 and 799 distinct main industries, allowing great precision in deciding where the buyout occurred.

While the majority of the research has available more private equity transactions due to a global focus, we have a more complete picture of the investment activity in choosing to explore Norway, due to a well-kept dataset. For instance, the data used by Aldatmaz and Brown (2018), rely on limited partnership investors reporting their data to Burgiss, possibly yielding a less complete picture of the private equity universe. As mentioned, they do have the advantage of detailed information for the transactions that are reported. Finally, we have available investment data for a long time period, as well as for very recent years. In contrast, much research relies on older data due to infrequently updated databases.

4. Hypotheses

From the discussion of related literature in chapter 3, we have seen that the majority of research points in the direction of higher performance for industries with buyout activity. To the best of our knowledge, there is limited research on these effects in single nations, apart from the US, with Norway being no exception. Based on the preceding arguments, this leads us to believe that buyout industry outperformance is indeed the case for the Norwegian economy as well. We thus propose the first of two hypotheses to assess research question one:

H1: Industries with presence of buyout activity outperform industries with no buyout activity

Following our initial hypothesis, we find it natural to suspect that the outperformance of industries experiencing buyouts is higher for industries with comparatively high buyout activity than industries with lower buyout activity. Furthermore, in the work of Bernstein, et al. (2017) it was found that the difference was economically significant, although not all results were statistically significant. We therefore test:

H2: Industries with the highest buyout activity have the highest outperformance

Research by Aldatmaz and Brown (2018) suggests that companies within the same industry absorb positive spillover effects created by private equity investment. We desire to build on this and the two aforementioned hypotheses. We bring to light the question of whether we can identify positive spillover effects on close competitors of the portfolio companies, or if the effect has to be attributed to the industry as a whole. We thus test:

H3a: Buyout activity creates positive spillover effects mainly for close competitors

H3b: The benefits of spillovers from buyouts are industry wide

There are three crucial steps in order to test these hypotheses. First, we create two unique datasets based on the ACPE investment data and SNF accounting data. Next, statistical methods are applied to the data and ultimately, the results are analysed. In the following chapters, these steps are explained in detail.

5. Data

5.1 Sample Selection

A thorough sample selection process is a crucial step in ensuring reliable data, which in turn ensures analyses of higher credibility. There are two distinctive components to this specific selection process: the gathering of 1) accounting data for all Norwegian companies and 2) investment data on all buyouts of Norwegian companies conducted by Norwegian private equity firms. These two sets of data are then combined to form the complete dataset and then customised, conditional on the specific analysis to be conducted.

The database of accounting- and company information for all Norwegian companies, compiled by the Centre for Applied Research (SNF) at the Norwegian School of Economics (NHH) and additional staff members at NHH, establishes the foundation for the empirical aims of this thesis. The database contains unbalanced panels of both consolidated- and unconsolidated accounts, as well as company-level industry information and additional information for the years 1992-2015 (Berner, et al., 2016)[2]. The Brønnøysund Register Centre submits the data annually via Bisnode D&B Norway AS and in collaboration with Menon Business Economics AS. The data received by SNF are often inconsistent and thus undergoes extensive quality assurance in order to be organised in accordance with the structure of the Accounting Act.

The second crucial component of the sample development is the Argentum Centre for Private Equity (ACPE) database[3], tracking all private equity transactions in the Nordic region (Argentum, 2012). Argentum, NHH and private equity industry players, including BAHR, Energy Ventures, HitecVision, Northzone Ventures, Norvestor Equity and PwC, founded the database in 2012 as a collaborative effort. It consists of portfolio-company level information, including organisational number, type of private equity transaction, the specific private equity firm and fund that invested in the company, investment- and exit dates, and exit type.

The initial step is to extract all potentially relevant transactions labelled as buyouts of companies headquartered in Norway, acquired by Norwegian private equity firms. In total, 288 observations are extracted and each of these are assigned a unique ID. Following the initial filtration ensues an extensive verification and information gathering process. We supplement

[2] The year 2015 was added to the dataset after the publishing of the referenced working paper.
[3] We thank Carsten Bienz for supplying the ACPE dataset.

missing investment information with external sources, in which press releases and information provided on the private equity firm's websites are the preferred choice. In situations where these sources are inadequate, news articles and other sources are reviewed. Next, we discard observations we are unable to use. The most frequent justification for a removal is, by a good margin, observations being incorrectly labelled as buyouts, when they in reality are ventures, growth, etc. As an example, all transactions carried out by Verdane Capital are removed due to a myriad of sources labelling Verdane as a venture capital fund[4], including Verdane themselves. Other reasons include, but is not limited to, investment year being outside 1992-2015, unattainable investment information, double counts of the same transaction, or the portfolio company actually being headquartered outside Norway. For instance, ODLO Sports Group was removed because it has been headquartered in Switzerland \since 1986[5]. This totals 88 observations dropped, thus far leaving us with exactly 200 observations.

In order to match the ACPE data with the SNF accounting data, we take advantage of the unique combinations of organisational numbers and years. The latter is already covered through the private equity investment date, which will be used as the matching year when the datasets are merged. We collect both the highest level of consolidated accounts, where available, and the most representative unconsolidated accounts. For the analysis of industry performance it is highly important to assign the most representative industry to the buyout, while the analysis of competitors require the most representative accounting numbers on which to match when employing the matching procedure in chapter 5.3. As discussed by Bienz (2016b), the typical buyout involves levering up an empty holding company and have this merge with the target company. This is due to Norwegian corporate law restricting the use of target firm cash flow to service the debt amassed. Consequently, we make use of unconsolidated accounts for the industry analysis and both unconsolidated and consolidated accounts for the competitor analysis, depending on availability and representativeness. Many of the organisational numbers are already available in the ACPE dataset, while the remaining are extracted through extensive searches in the SNF database in combination with other accounting databases[6]. In addition, we also verify all the underlying companies behind the gathered organisational numbers with the SNF database to ensure that the numbers for pivotal variables do in fact exist.

[4] See, for example: (Argentum, n.d.) and (Verdane Capital, n.d.)
[5] See https://www.odlo.com/no/en/about-us or ODLO under the "current investments" page for Herkules Capital's webpages
[6] See https://www.proff.no/ and https://www.regnskapstall.no/

Eight observation are removed owing to missing organisational numbers or data in the SNF database being lacking, unusable or simply unrepresentative. As an example of the latter argument, in some cases the only available accounting data are for the private equity firm- or fund itself, owning the underlying company. This is unrepresentative, since the private equity firms'- or funds' accounts may contain multiple buyouts. For the sample to be used in research question one, we need to note one specific adjustment. Namely, 22 observations do not have available the necessary industry classification and are thus omitted, resulting in a sample of 170 buyouts being used in the industry analysis.

For the sample relating to research question two, five observations are removed due to accounting data only being available from one or two years *after* buyout, something we deem unrepresentative when identifying competitors. Additionally, we restrict the sample for the competitor analysis to the period 1993-2012 due to no buyouts taking place in 1992, and since we need accounting data for three years post buyout to be available in order to run all our models. The preceding discussion leaves us with a sample of 152 buyouts to be used for matching competitors to the buyouts in our sample.

5.2 Sample Description

Table 1 provides information on buyout transactions of Norwegian companies by private equity firms headquartered in Norway, distributed by respective industry and year. The 170 buyouts occurred between 1993 and 2015, and reveal an upward sloping trend in the number of buyouts across the period. The table depicts a structural shift in buyout activity in 2006, in which there was comparatively little activity in 1993-2005 and a boom from 2006. To put this into perspective, the number of buyouts in 2006 was almost equal to the accumulated buyouts in the three preceding years. Hence, there was a substantial increase in the number of buyouts in the last years leading up to the global financial crisis, with 2007 being the year with the highest occurrence of buyouts in our sample, seeing 19 buyouts. Furthermore, 2006-2015 experienced 2.5 times as many buyouts as 1993-2005, despite a shorter period. This is in line with much of the discussion in chapter 2, once again illustrating that the Norwegian market is relatively young and is experiencing growth in more recent times.

We observe that all 14 industries have experienced at least one buyout during the 24 years the sample covers, but note that the primary-, energy/water/sewage/utility-, shipping-, finance/insurance-, and research and development industries in total only experienced one buyout each. Furthermore, manufacturing industries have the highest concentration of buyouts with 45 transactions, followed by trade with 35, general services with 27, and telecom/IT/media with 26. Hence, four industries account for the majority or 78% of all buyouts. This distribution is somewhat similar to the distribution discussed in chapter 2.2, where three industries accounted for 62.5% of total buyout transactions or 81.3% when looking at the four largest. The largest of these three industries is petroleum, which is the fifth largest in our sample, while IT is the second largest and the fourth largest in our sample. However, we observe most of the IT and petroleum investments are occurring in recent times, supporting the trend discussed in chapter 2.2. It has to be noted that industry classifications somewhat differ. For instance, many of the buyouts in the third largest industry from chapter 2.2, business services and industry services, likely fall under such as manufacturing services, trade and general services in our sample. Additionally, our numbers are accumulated for 1993-2015, while the 62.5% is for 2017. Nonetheless, it is still an interesting comparison.

In contrast to the high concentration of buyouts in few industry groups, the more detailed classifications yield a more dispersed distribution among individual industries. For the finest industry classification, the 170 buyouts are scattered across exactly 100 individual, unique industries. The single, most heavily represented industry has experienced 10 buyouts, as a contrast to the 45 given the coarsest classification. This industry is labelled, "other services in connection to oil extraction", which makes sense for an oil nation such as Norway.

The 170 buyouts in the sample are conducted by 16 different private equity firms, in which Norvestor Equity were responsible for the largest amount, conducting 40 buyouts. Following Norvestor are HitecVision with 30 buyouts and Herkules Capital with 26 buyouts. Furthermore, we find that 89 of the buyouts are concentrated in the region consisting of the counties Oslo, Akershus and Østfold, while 62 buyouts occurred in the region consisting of Rogaland, Hordaland, Sogn and Fjordane, and Møre and Romsdal. The mean investment year in the sample is 2007, while the median is 2008. In total, 105 buyouts were exited during the entire sample period, and 44 of these were trade sales. For the holding period of the already exited buyouts in our sample, we determine that the mean is 5.08 years, and the median 5 years. Finally, the mean size of the portfolio companies at the time of buyout, measured as total assets in NOK, is 247 million and the median size is 123 million.

Table 1. Buyout Transactions by Industry

The table depicts the number of buyout investments distributed by industry. The numbers at the top of the columns represent the code used for each industry group based on SN2007, which is the standard used for classifying industries, implemented January 1st 2009 (we refer to chapter 5.3 for a further description of the industry codes). They are: Primary industries (1), Oil/Gas/Mining (2), Manufacturing industries (3), Energy/ Water/Sewage/Utility (4), Construction (5), Trade (6), Shipping (7), Transport, Tourism (8), Telecom, IT, Media (9), Finance, Insurance (10), Real Estate, Services (11), General Services (12), Research and Development (13), Public Sector, Culture (14).

	Industry Group by SN2007														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	**Total**
Investment Year															
1992	-	-	-	-	-	-	-	-	-	-	-	-	-	-	**0**
1993	-	-	-	-	-	1	-	-	-	-	-	-	-	-	**1**
1994	-	-	1	-	-	-	-	-	-	-	-	-	-	-	**1**
1995	1	-	-	-	-	2	-	-	1	-	1	-	-	-	**5**
1996	-	-	3	-	-	1	-	-	-	-	-	-	-	-	**4**
1997	-	-	4	-	-	1	-	-	-	-	1	1	-	-	**7**
1998	-	-	1	-	-	1	-	-	-	-	-	-	-	-	**2**
1999	-	-	2	-	-	1	-	-	-	-	-	-	-	1	**4**
2000	-	-	-	-	-	-	-	-	-	-	-	3	-	-	**3**
2001	-	-	1	-	-	2	-	-	-	-	-	1	-	-	**4**
2002	-	-	2	-	-	-	-	-	1	-	-	-	-	-	**3**
2003	-	1	1	-	-	-	-	1	1	-	-	1	-	-	**5**
2004	-	-	2	-	-	1	-	-	-	-	1	2	-	-	**6**
2005	-	1	-	-	-	2	-	-	-	-	-	1	-	-	**4**
2006	-	-	6	-	1	3	-	1	-	-	-	-	-	2	**13**
2007	-	2	3	-	-	6	-	-	1	-	-	4	-	3	**19**
2008	-	2	1	1	-	1	-	-	6	-	-	3	-	-	**14**
2009	-	-	3	-	-	-	-	-	4	-	-	1	-	-	**8**
2010	-	1	3	-	-	2	-	-	4	-	-	3	-	-	**13**
2011	-	1	1	-	1	2	-	-	1	-	-	1	1	1	**9**
2012	-	1	6	-	1	3	-	-	2	-	-	2	-	-	**15**
2013	-	2	3	-	-	2	-	-	1	1	-	1	-	-	**10**
2014	-	3	1	-	-	4	-	-	1	-	1	2	-	-	**12**
2015	-	-	1	-	-	-	1	2	3	-	-	1	-	-	**8**
Total	**1**	**14**	**45**	**1**	**3**	**35**	**1**	**4**	**26**	**1**	**4**	**27**	**1**	**7**	**170**

5.3 Propensity Score Matching

In order to assess whether spillover effects exist for close competitors of portfolio companies receiving private equity backing, we need to identify a sample of close competitors. Additionally, we need to identify a control group that is not affected by buyout activity. Hence, it will serve as a benchmark for the counterfactual effect[7]. We hypothesise that distant competitors of portfolio companies be unaffected by buyout activity, since they should be considerably less likely to observe- and take it into consideration. Therefore, we intend to identify pairs of close- and distant competitors for each unique buyout transaction. One procedure that may help us achieve this goal is Propensity Score Matching (PSM) as proposed by Rosenbaum and Rubin (1983). Before we explain in detail our matching procedure, we provide an explanation of PSM.

The propensity score can be defined as the probability of receiving treatment, in our case private equity backing, conditional on observed characteristics (Caliendo & Kopeinig, 2008). As explained by Rosenbaum and Rubin (1983), the propensity score is one possible balancing score, more specifically the coarsest function that is a balancing score. It is advantageous when one is unable to obtain random samples, since PSM attempts to simulate the randomised assignment into treatment- and control groups (Gertler, et al., 2011, p. 109). Consequently, it is applicable to this given situation, considering we have observational data, where treatment was not randomly assigned. Furthermore, Gertler, et al. (2011, p. 108) highlight PSM as being useful when matching on multiple characteristics, since one avoids "the curse of dimensionality"[8].

Caliendo and Kopeinig (2008, p. 9) point out that multiple matching algorithms exist for PSM, namely nearest neighbour, caliper and radius, stratification and interval, kernel and local linear, and weighting. In support of nearest neighbour matching, they argue that it is the most straightforward approach to PSM. Furthermore, it implies that we obtain the match that is indeed the closest competitor as decided by PSM and reduces the risk of finding bad matches. For instance, the nearest neighbour could be a good match, while the second nearest neighbour

[7] The counterfactual is the course of development the treatment (close competitors) is believed to follow had the buyout not occurred.

[8] The inability of obtaining matches when incorporating many variables, especially if they are continuous. Thus, creating many dimensions in the matching.

could be a terrible match. Hence, this is our chosen matching option and, as we will see in the proceeding sections, it serves our strict requirements well.

The concept of PSM can be formalised with the following equation (Rosenbaum & Rubin, 1983, p. 42-43):

$$e(x_i) = P(PE_i = 1|x_i) \qquad \textit{(5.2),}$$

where $e(x_i)$ is the estimated propensity score for company i (i = 1, 2,…, N), x_i is the vector of observed covariates and $PE_i = 1$ if it is a buyout. The vector of covariates is based upon observables that likely affect the decisions of GPs when selecting targets for buyout. In the matching procedure, we therefore employ the natural logarithm of size[9], leverage ratio, liquidity ratio and EBIT margin, which are contained in the vector of covariates, x_i. We refer to Appendix A for a complete description of variables. Unfortunately, we are unable to control for unobservable effects such as quality of leadership at the portfolio company, GP ability, portfolio company adaptability to change, etc.

A prerequisite for the analysis is to ensure companies have available three years of accounting data post buyout. We therefore restrict the PSM model to finding matches with three years of available accounting data post buyout. Additionally, we winsorize all continuous variables at the 98% level[10] in order to reduce the effect of extreme outliers. As an example, we have observed debt being much larger than total assets and also many values having extremely large negative values.

When choosing functional form of the binary treatment case, Caliendo and Kopeinig (2008) argue that probit and logit commonly return the same results, although density mass in the bounds is higher for logit. For the purpose of this thesis, logit is applied. Since we implement PSM using one nearest neighbour, we are also able to match without replacement, resulting in unique matches. Common support, also known as the overlap condition, is imposed to ensure that one avoids the situation of perfect predictability of treatment, *PE*, given the covariates, *x* (Caliendo & Kopeinig, 2008). Finally, we utilise heteroskedasticity-robust standard errors as proposed by Abadie and Imbens (2006).

[9] Total assets are used as a proxy for the company size.
[10] Winsorizing at the 98% level involves limiting extreme values at the 1st and 99th percentile, setting them equal to the next most extreme value within the 98% interval.

The matching procedure is repeated for every industry-year combination, to secure matches be found in the same industry and year as the given buyout occurred. This approach should yield matches that are more comparable and we are spared situations where, for instance, a buyout in the agriculture industry in 1995 is assigned a match in the ICT industry in 2012. Fortunately, the SNF database includes industry breakdowns following Standard Industrial Classification (NACE) (Berner, et al., 2016). These are five-digit codes and as a consequence of changes in the practice for classification, starting from January 1st 2009, there are two available standards. The SN2002 code is missing for newly established companies from 2008 and the SN2007 code is missing for companies that only exist prior to 2008. Since we restrict the PSM to each specific year and industry, we are able to "bypass" the issue of NACE codes changing between 2007/08, since we use the SN2002 code up to and including 2007 and the SN2007 code from 2008. This yields the most matches and arguably the most representative matches. There exist three separate levels of industry classifications for both SN2002 and SN2007, i.e. three levels of fineness. For SN2007 the classifications yield 14, 87 and 799 unique categories, with existing data, for respectively coarsest to finest.

We run the entire matching process for both the coarsest and finest industry classifications. The finest classification will certainly yield the most meaningful results, since it involves considerably more specific industry descriptions, thus culminating in the most representative matches for each buyout. As a real example from our dataset, one would be at risk of matching a producer of oilrigs and –platforms with a producer of bread, when using the coarsest classification. This is possible due to the fact that each category of the coarsest classification consists of on average close to 60 sub-categories. When PSM is run for the coarsest classification, matches can thus be assigned in any of these subcategories. Hence, the finest classification will be applied to the main analysis of competitors, while the coarsest classification is used for comparison.

Important in ensuring quality matches is the distinction of matches into close- and distant competitors. For the purpose of this thesis, close competitors will be defined as the nearest neighbour of the buyout, resulting from the criteria imposed on the PSM model. Identifying distant competitors is a more delicate procedure, considering the mechanics of implementing PSM in statistical software, where no option for finding distant matches is available. Although we seek distant matches, we do require the same industry classification and year as the buyout. While the match has to be distant, it must be within the limits of reasoning. The general idea of the approach is to seek matches that are *different* in propensity scores. Matches being different in propensity scores imply, in the context of PSM, that the match should be less similar in terms of the covariates and thus less likely to be a candidate for buyout. Caliendo and Kopeinig (2008) point out that one can use caliper matching to impose a maximum propensity score distance, as to avoid terrible matches. Similar to caliper matching, we impose a maximum distance in propensity scores, which we set to 0.1. This deters PSM from matching e.g. Elkjøp[11] with a tiny local electronics shop in a remote Norwegian town. We then calculate the distance in propensity scores for all companies that are being evaluated for matching relative to the buyout target. The distant competitor is then the match with the longest distance, below the cut-off level of 0.1. This can be thought of as the furthest neighbour, within a reasonable limit.

As mentioned, we conduct PSM with 1-to-1 nearest neighbour matching. This is rooted in the fact that the current specification of PSM is unable to find matches for a modest amount of the buyouts. Furthermore, many individual industries have comparatively few observations, making it difficult in many cases to find even a single neighbour. Finally, insisting on multiple matches would result in lower quality matches and higher bias (Caliendo & Kopeinig, 2008). Founded in the preceding discussion of this chapter, the matching procedure leaves us with 96 pairs of close- and distant neighbours. These 96 pairs are the foundation of the competitor analysis in chapter 7.2.

6. Methodology

6.1 A Note on Treatment Effects and Causality

Angrist and Pischke (2008, chapter 2) purposely demonstrate, by conducting a simple analysis of mean health status and taking the results at face value, that hospitals make people sicker. This is intuitively somewhat absurd, but it is rooted in the fact that people are hospitalised (treated) due to being sicker than non-hospitalised individuals (control group). This example illustrates the issues and difficulties in differentiating between what is a result of treatment and what is a result of selection. The concept can be mathematically formalised as in (Angrist & Pischke, 2008, chapter 2):

[11] Elkjøp is a massive chain of electronics retail stores in Norway and also a part of our sample of buyouts.

$$E[Y_i|D_i = 1] - E[Y_i|D_i = 0] = E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 1] \\ + E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0] \quad (6.1.1),$$

where the left hand side of the equation is the combined effect, the first two components on the right hand side comprise the average treatment effect on the treated and the two last components comprise the selection bias. Said differently, the total effect is the sum of treatment and selection bias.

Although arguably less grim than the introductory example, the same differentiating problem emerges in most research on private equity. It relates to whether the difference in performance between treatment and control should be attributed to the actual performance enhancements created by private equity or the superior abilities of GPs to select winners. Lerner and Schoar (2005) describes selection bias in private equity research as an "almost inevitable consequence" and a wide range of additional papers address the issue (see, for example (Bernstein, et al., 2017), (Bienz, 2016a), (Bloom, et al., 2015), (Davis, et al., 2014) and (Kaplan & Strömberg, 2009)). Furthermore, what is commonplace between such papers is that the issue on selection versus treatment is a hard one to overcome.

The two subchapters that follow address the methodology to be employed upon the hypotheses. Said methodological approach has been designed in an effort to best address the issues regarding selection bias and towards isolating the actual effect of improvements private equity is believed to bring.

6.2 Research Question One

The effort towards exploring the impact of private equity on industry performance begins with the creation of industry-region-year observations, e.g. the shipping industry in western Norway in 1994. These observations consist of aggregate numbers of all the firms that operated within that specific industry-region-year combination. This allows us to control for industry-, region- and year fixed effects, necessities in verifying robustness of results and providing evidence supporting the effect being causal. We employ several specifications of fixed-effect panel regressions, with equation 6.2.1 that follows being the most decorated specification:

$$y_{iry} = \beta BOindustry_{iry} + \psi_{ir} + \xi_{iy} + \varepsilon_{iry} \qquad \textit{(6.2.1)},$$

where *i* indexes the industry classification, *r* indexes the region and *y* indexes the year. y_{iry} is the performance metric of interest, $BOindustry_{iry}$ is equal one if the industry is a buyout industry and respectively ψ_{ir} and ξ_{iy} are sets of dummy variables encompassing fixed effects for industry-region and industry-year. Varying sets of these fixed effects are included in each specification. ε_{iry} is the error term, containing unobserved effects. We do not use industry-year fixed effects for the analysis based on the finest classification, due to Stata[12] setting a limit on 11,000 variables. However, we do use clustered standard errors by industry-year, to take some account for this, and to make the standard errors as robust as possible (Wooldridge, 2013, p. 483).

As discussed in the work of Wooldridge (2013), unbiased estimators of the ceteris paribus effect of explanatory variables are dependent on whether or not the Zero Conditional Mean (ZCM) holds. This assumption is crucial for regression models and mathematically this implies $E\left[\varepsilon_{iry}\middle|BOindustry_{iry}\right] = 0$ for our model. Our proposed fixed effects regressions with such rich controls, that capture unobserved heterogeneity, yield greater plausibility of the ZCM holding. This implies that there is a greater plausibility of the selection effect being captured by said unobserved heterogeneity and thus not correlated with the variable, *BO Industry*, through the error term. Additionally, controlling for industry-region fixed effects enables us to control for, e.g. the oil industry in Stavanger being very different from the oil industry in another region. Furthermore, industry-year fixed effects allow controlling for shocks that occurred in the economy, e.g. the oil shock in 2014.

The identification process revolves around classifying industries into buyout industries and non-buyout industries. Following Bernstein, et al. (2017), we intend to classify industries having experienced a buyout in a given number of years as a buyout industry; otherwise it is a non-buyout industry. Traditionally, the average holding period of portfolio companies has been between three to five years (Preqin, 2015). In 2008, it was 4.1 years, while it in 2014 increased to 5.9 years. The average holding period for our sample is 5.08 years, and thus an industry is labelled as a buyout industry if at least one buyout has occurred the last five years. Furthermore, we aim to distinguish industries with high- and low buyout activity, in order to

[12] Stata is a statistical software package for data science.

address whether industries with high frequency of buyouts have the highest outperformance. This is accomplished by calculating the mean value of buyout occurrences per industry as the cut-off value, where industries above (below) said cut-off value are labelled *BO High* (*BO Low*). This involves replacing the *BOindustry* variable in equation 6.2.1 in favour of *BO High* and *BO Low*.

We largely build our analysis of industry performance around the five-digit NACE code, which was previously explained in chapter 5.3. We do not make use of the sector classification, since one of the categories is simply "other", which may contain a variety of different industries and restrict us from identifying the true industry. This category also represents a substantial 27% of the observations. Although the number of buyouts prior- and post 2008 is roughly the same and the total number of buyouts for SN2002 and SN2007 also being approximately the same, the coarsest SN2007 classification has the advantage of 14 classifications, instead of 12, something we find more representative. Based on this, we end up adopting the SN2007 industry classifications. However, we also rerun the analysis with SN2002 classification, something we come back to in chapter 7.1.

As discussed in chapter 5.3 the unique dataset enables three levels of industry classifications. We suspect that it is increasingly random which industries GPs select for investment when we use finer classifications, i.e. the sub-classifications within the coarser classifications. As an exemplification of this point, a private equity firm may very well specialise in trade (one of the 14 coarsest classifications), but it is likely random which specific type of retail they select for investment. Our relatively small sample suggests this to be justified, considering it includes 10 different types of retail at the finest classification. In other words, investments are significantly more dispersed among the mid and low industry classifications. With this in mind, we follow the initial analysis and redo it with the two finest classifications. Hence, we change the industries contained in subscript i of equation 6.2.1. Since the number of observations is the product of the given unique years, industry classifications and regions, the number of observations increases as we use progressively more detailed classifications for industries.

To measure the potential effects of private equity on industry performance, we employ metrics similar to those that have been adopted in the literature previously, since this allows for greater transparency when comparing research in the field. We refer to Appendix A for a detailed explanation of all performance metrics. Considering we are exploring the impact on overall industry performance, a topic of interest for both academics and policy makers alike, we strive towards employing comprehensible measures. These are based on both the related literature discussed in chapter 3 and said comprehensibility. Hence, we investigate the effect on total output, value added and real/fixed capital.

As a more original contribution to the research field, we also measure the growth in the number of companies, capturing establishment of new players. We create a dummy variable equal to one for all firms in all years of operation before aggregating the initial observations into industry-region-year observations. When the set is aggregated, it provides us with the number of active companies for a given industry-region-year combination. This yields data that are completely representative for our unique dataset, instead of importing an external dataset, which may be highly unrepresentative when considering that industry classifications may be conflicting.

6.3 Research Question Two

In order to address whether competitors of portfolio companies are affected by buyout activity, we take the created samples of close- and distant competitors that are thought to be comparable to the actual portfolio companies and apply difference-in-differences (DD) regressions as explained in (Angrist & Pischke, 2008, pp. 175). The general model specification employed in the competitor analysis follows in equation 6.3.1:

$$y_{it} = \beta_1 Comptype_{it} + \beta_2 Dyear_{it} + \beta_3 Comptype_{it} * Dyear_{it} + \lambda_j + \varepsilon_{it} \quad \textit{(6.3.1)}$$

where *i* indexes the individual company, *t* indexes time and *j* indexes the specific industry group. y_{it} is the performance metric of interest. $Comptype_{it}$ is a dummy variable equal to one if the company is a close competitor and zero if it is a distant competitor. $Dyear_{it}$ is a dummy variable equal to one if the year is respectively one, two or three years post buyout, depending on the model specification, and zero if it is the buyout year. $Comptype_{it} * Dyear_{it}$ is the interaction term, containing the concrete treatment effect. λ_j is a set of dummy variables equalling one if the industry is industry j. ε_{it} is the error term, containing unobservable effects. The only two variables changing between the specifications is $Dyear_{it}$, depending on which year post buyout we analyse, and λ_j, depending on whether we include fixed industry effects.

Although $Comptype_{it} * Dyear_{it}$ does not in itself change, it changes as a result of $Dyear_{it}$ changing.

Lechner (2010) describes the difference-in-differences method as a “research design for estimating causal effects” (p. 167). Furthermore, Angrist and Pischke (2015) explain the usefulness of DD in the absence of random assignment and point out that credible instrumental variables are rare to stumble upon. Finding credible instruments in the private equity research field is no exception. The method can be implemented both manually and through regression (see equation 6.3.1) and is thus highly applicable when one has a representative counterfactual control group available.

The rationale for using DD in our case is that we hypothesise close competitors to be affected by private equity activity, while distant are not, since the close competitors are much more likely to notice the activity and change their behaviour accordingly. In other words, competitors work as a proxy for the counterfactual, i.e. the rate close competitors are believed to have progressed in the absence of private equity. The coefficient of interest is β_3, the coefficient for the interaction term between the year indicator and the indicator for treatment group. This coefficient is known as the average treatment effect (Wooldridge, 2013, pp. 457). In our specification, it measures the treatment effect of being the close competitor of a company that receives private equity backing. In other words, it can be viewed as the causal spillover effects created by private equity. We also control for fixed industry effects, to further isolate the effect of private equity.

Before we proceed to the results chapter, we define performance metrics along which performance of close- and distant competitors will be measured. We find it befitting to investigate performance in relation to financials, operations and distress risk, since different stakeholders are likely to be interested in a diverse pool of measures. Moreover, much based on typical performance metrics in analysing portfolio companies and inspired by related literature described in chapter 3, we analyse the following: Return on Equity (ROE), Return on Assets (ROA), and Free Cash Flow (FCF) to total assets as our financial measures; total income, profitability ratio, fixed asset ratio, and fixed asset turnover ratio as operational measures; leverage ratio, and interest coverage ratio as distress risk measures. Again, we refer to Appendix A for a detailed explanation of all performance metrics.

7. Empirical Results

7.1 Impact of Buyouts on Industry Performance

In the following five subchapters, we will be exploring the impact of buyout activity on respectively growth in total output, value added, fixed capital and total number of companies. The main analysis for each performance metric includes six specifications, using the coarsest industry classification. We impose increasingly strict specifications and then perform the analysis while differentiating between high- and low buyout activity. Next, the entire analysis is repeated for the two finest industry classifications to provide robustness. Finally, we discuss the overall results, relate them to hypothesis one and two formulated in chapter 4 and further address causality concerns.

7.1.1 Total Output

We start by examining whether private equity has an impact on total industry output. The results are presented in Table 2, which implements six different variations of specification 6.2.1 discussed in chapter 6.2. We see from column (1) and (2) that buyout industries are positive economically- and statistically significant different from non-buyout industries. This result holds for column (3), where we control for both industry-year and industry-region fixed effects. This specification is thus the strictest and of highest interest. The coefficient of *BO Industry* is 0.38 and significant at the 1% level. Hence, buyout industries have a 0.38 percentage points higher growth in total output than non-buyout industries. This could indicate that industry peers, after observing private equity backed companies grow their sales, answer by increasing own sales to stay competitive. The results are similar to Bernstein, et al. (2017), who find that buyout industries have a total output growth rate 0.863 percentage points higher than non-buyout industries.

Next, we divide buyout activity into high- and low categories. Given the Wald tests in column (4) through (6), high buyout activity and low buyout activity are consistently significantly different at the 1% level. For column (6), an industry with high buyout activity achieves a 0.58 percentage point outperformance relative to non-buyout industries. We find no evidence of differences between industries with low buyout activity and no buyout activity, given column

Table 2. Impact of Buyout Activity on Total Industry Output

The table presents coefficient estimates of OLS panel data regressions of total output on PE ownership. An observation is an industry-region-year combination, using the coarsest industry classification of 14 industry categories, 7 region categories and 24 separate years. Total Output is defined as the sum of total income and change in inventory of goods. BO Industry is equal one if the industry is a buyout industry, while BO High and BO Low are equal one if the industry is a buyout industry and is respectively above or below the mean number of buyouts per industry. Fixed effects for the products of industry-year and industry-region are also included. Finally, $BO_H = BO_L$ is a Wald test for equality. See Appendix A for descriptions of all variables. Standard errors are heteroskedasticity-robust and in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1) Total Output	(2) Total Output	(3) Total Output	(4) Total Output	(5) Total Output	(6) Total Output
BO Industry	2.20***	2.03***	0.38***			
	(0.11)	(0.09)	(0.09)			
BO High				2.45***	2.27***	0.58***
				(0.14)	(0.10)	(0.13)
BO Low				1.65***	1.31***	-0.01
				(0.13)	(0.18)	(0.08)
Constant	13.64***	13.98***	12.35***	13.64***	13.98***	12.32***
	(0.43)	(0.19)	(0.48)	(0.43)	(0.19)	(0.46)
Industry-Year FE	X		X	X		X
Industry-Region FE		X	X		X	X
$BO_H = BO_L$				0.00***	0.00***	0.00***
N	2,340	2,230	2,230	2,340	2,230	2,230
R2	0.49	0.54	0.87	0.49	0.54	0.88

(6). These findings are in contrast to Bernstein, et al. (2017), who find the difference in total output growth between high- and low buyout activity to be far from significant.

In order to provide robustness, we redo the analysis with the two finest industry classifications. Table B1 and B5 in Appendix B respectively report the output based on the second finest classification and the finest classification. The results of the second finest classification are largely similar to the results in the coarsest analysis, apart from *BO Low* becoming positive and significant, and there no longer being a significant difference between *BO High* and *BO Low* in column (4). Inspecting table B5 reveals several evident observations[13]. First, the economic magnitude of *BO Industry* in column (3) and *BO High* in column (6) greatly reduces compared to the coarsest analysis. Considering that the controls are less strict in these specifications as compared to the coarsest analysis, the change is further emphasised. Second,

[13] As a reminder, we point out that Year FE is used instead of Industry-Year FE when employing the finest classification.

BO High and *BO Low* in column (5) are now almost identical. Finally, in column (6) we see that the difference in high- and low buyout activity is now significant at the 1% level in favour of *low* buyout activity. Hence, our findings hold up well for specifications (1)-(3), but show inconsistencies for (4)-(6) under increasingly detailed industry classifications.

7.1.2 Value Added

The results in table 3 greatly resemble the results in subchapter 7.1.1, with most specifications yielding economically- and statistically significant results across the board. The coefficient on *BO Industry* is 0.41 and significant at the 1% level, signifying a 0.41 percentage points higher growth in value added for buyout industries relative to non-buyout industries. This could be a consequence of industry participants increasing their sales or reducing their costs as a response |to the buyout activity in their industry. In column (4) through (6), all variables are significant at the 1% level, apart from *BO Low* in column (6), which is insignificant. Moreover, the Wald test yields a significant difference between industries with high- and low buyout activity at the 1% level.

Table 3. Impact of Buyout Activity on Industry Value Added

The table presents coefficient estimates of OLS panel data regressions of value added on PE ownership. An observation is an industry-region-year combination, using the coarsest industry classification of 14 industry categories, 7 region categories and 24 separate years. Value added is defined as the sum of total income and change in inventory of goods less cost of goods sold. The remaining variables are defined in Table 2. Standard errors are heteroskedasticity-robust and in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1) Value Added	(2) Value Added	(3) Value Added	(4) Value Added	(5) Value Added	(6) Value Added
BO Industry	2.20^{***}	1.83^{***}	0.41^{***}			
	(0.11)	(0.08)	(0.09)			
BO High				2.45^{***}	2.03^{***}	0.62^{***}
				(0.14)	(0.09)	(0.13)
BO Low				1.63^{***}	1.25^{***}	0.01
				(0.13)	(0.17)	(0.07)
Constant	13.10^{***}	13.51^{***}	11.93^{***}	13.10^{***}	13.51^{***}	11.90^{***}
	(0.46)	(0.20)	(0.52)	(0.46)	(0.20)	(0.51)
Industry-Year FE	X		X	X		X
Industry-Region FE		X	X		X	X
$BO_H = BO_L$				0.00^{***}	0.00^{***}	0.00^{***}
N	2,332	2,224	2,224	2,332	2,224	2,224
R2	0.47	0.54	0.87	0.48	0.54	0.88

Similar to subchapter 7.1.1, we focus our attention on the finest industry classification, this time referring to Table B6. Again, the Wald test in specification (5) displays an insignificant difference in high- and low buyout activity, while the test in (6) finds a significant difference at the 5% level in favour of *low* buyout activity industries. Overall, evidence indicates outperformance in favour of buyout industries, with results being robust. However, there are inconsistencies when differentiating high- and low-buyout activity. Furthermore, the findings are generally in line with Bernstein, et al. (2017). They also find clear evidence of buyout industries outperforming non- buyout industries in terms of growth in value added, as well as a significant difference between high- and low buyout activity at the 5% level.

7.1.3 Fixed Capital Growth

Results in Table 4 provide overall evidence of buyout industries outperforming non-buyout industries in terms of fixed capital growth. In column (3), the coefficient of *BO Industry* is 0.39 and significant at the 1% level. Hence, buyout industries have a 0.39 percentage points higher growth in fixed capital than non-buyout industries. One valid explanation could be that industry peers take note of buyout activity and increase their investment in real capital as to stay competitive in the long run. In addition, we find high- and low buyout activity to be significantly different at the 1% level, except when we only control for industry-region fixed effects. In this scenario, the difference is only significant at the 10% level.

Next, we turn our attention to the results for the second finest- and finest classifications in respectively Table B3 and B7. When employing the second finest classification, the results remain roughly the same. Notable changes are *BO Low* in column (6) becoming significantly different from non-buyout industries at the 1% level and the Wald test in column (4) now only being significant at the 10% level. Moving to the finest classification, we find that most specifications experience clear reductions in magnitude of coefficients. Furthermore, we are no longer able to identify significant differences between high- and low buyout activity in columns (5) and (6).

In sum, the findings on fixed capital growth seem to be aligned with Bernstein, et al. (2017). They find buyout industries to have a gross fixed capital formation growth 1.336 percentage points higher than non-buyout industries. However, their Wald test for equality yields far from significant results. To be precise, it yields a p-value of 0.798, which is surprisingly close to

Table 4. Impact of Buyout Activity on Industry Fixed Capital Growth

The table displays coefficient estimates of OLS panel data regressions of fixed capital growth on PE ownership. An observation is an industry-region-year combination, using the coarsest industry classification of 14 industry categories, 7 region categories and 24 separate years. Fixed capital growth is the natural logarithm of the sum of real property, machinery and plant, and ships, rigs, planes, etc. The remaining variables are explained in Table 2. Standard errors are heteroskedasticity-robust and in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1) Fixed Capital	(2) Fixed Capital	(3) Fixed Capital	(4) Fixed Capital	(5) Fixed Capital	(6) Fixed Capital
BO Industry	2.30^{***}	1.50^{***}	0.39^{***}			
	(0.11)	(0.09)	(0.10)			
BO High				2.53^{***}	1.59^{***}	0.57^{***}
				(0.15)	(0.11)	(0.15)
BO Low				1.79^{***}	1.22^{***}	0.05
				(0.13)	(0.16)	(0.08)
Constant	11.01^{***}	12.89^{***}	11.32^{***}	11.01^{***}	12.89^{***}	11.31^{***}
	(0.89)	(0.18)	(0.37)	(0.89)	(0.18)	(0.36)
Industry-Year FE	X		X	X		X
Industry-Region FE		X	X		X	X
$BO_H = BO_L$				0.00^{***}	0.05^{*}	0.00^{***}
N	2,351	2,232	2,232	2,351	2,232	2,232
R2	0.54	0.59	0.87	0.54	0.59	0.87

specification (6) in Table B7. On the other hand, these results are likely not comparable, since specification (6) applied a much finer industry classification and it included year fixed effects instead of industry-year fixed effects. The coarsest specification returns a difference significant at the 1% level.

7.1.4 Growth in Number of Companies

Output presented in Table 5 supply evidence that growth in the number of companies operating in buyout industries is significantly higher than non-buyout industries across the board. From column (3), the number of companies in buyout industries grows at a 0.17 percentage points higher rate than non-buyout industries. However, evidence of differences between high- and low buyout activity is split, with the strictest specification displaying no significant difference.

Table 5. Impact of Buyout Activity on Number of Companies per Industry

The table displays coefficient estimates of OLS panel data regressions of number of companies on PE ownership. An observation is an industry-region-year combination, using the coarsest industry classification of 14 industry categories, 7 region categories and 24 separate years. Number of companies is defined as the natural logarithm of the number of companies. The remaining variables are explained in Table 2. Standard errors are heteroskedasticity-robust and in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1) Number of Companies	(2) Number of Companies	(3) Number of Companies	(4) Number of Companies	(5) Number of Companies	(6) Number of Companies
BO Industry	1.45***	1.20***	0.17***			
	(0.06)	(0.06)	(0.04)			
BO High				1.54***	1.31***	0.20***
				(0.08)	(0.06)	(0.05)
BO Low				1.26***	0.88***	0.11***
				(0.08)	(0.13)	(0.04)
Constant	3.64***	4.90***	3.72***	3.64***	4.90***	3.72***
	(0.59)	(0.15)	(0.22)	(0.59)	(0.15)	(0.22)
Industry-Year FE	X		X	X		X
Industry-Region FE		X	X		X	X
$BO_H = BO_L$				0.01**	0.00***	0.17
N	2,391	2,252	2,252	2,391	2,252	2,252
R2	0.69	0.60	0.96	0.69	0.60	0.96

Seeing that the coefficient on *BO Industry* is significantly positive at the 1% level, it could be an indication that potential new entrants observe a specific industry doing well and thus provide strong incentives to establish in said industry.

Comparing these findings to the results for the second finest classification in Table B4 yield similar results, aside from some coefficients increasing in economic magnitude and some decreasing. Additionally, the difference between high- and low buyout activity in column (6) is now significant at the 1% level. Turning to Table B8 and the finest classification, coefficients remain strongly positive and significant, but with most coefficients having notably lower magnitude than the two coarser specifications. The Wald test in column (5) is now only significant at the 5% level, while it is far from significant in column (6). We are unaware of related literature exploring the effect of private equity on growth in the number of companies and thus have no basis for comparison.

7.1.5 Further Discussion

In sum, all evidence indicates that buyout industries outperform non-buyout industries in terms of growth in total output, value added, fixed capital and total number of companies. The evidence proves convincingly robust when we impose increasingly detailed industry classifications, moving all the way from 14 to 799 classifications. Hence, we conclude that clear evidence exists in favour of H1. In relation to H2, we find conflicting evidence. For the coarsest industry classification, the overwhelming majority suggest that industries with high buyout activity significantly outperform industries with low buyout activity. However, when employing the finest classification, column (5) for growth in total output, value added and fixed capital return the relationship insignificant. Additionally, column (6) for growth in total output and value added interestingly find that industries with low buyout activity outperform industries with high buyout activity. We are thus unable to provide a single, unambiguous conclusion in regards to H2.

Although we find clear evidence in support of H1 and some evidence in support of H2, there exists an urgent need to address the causality concerns. More specifically, whether the established effects are due to private equity backing or selection. First, our rich set of controls for unobserved industry-, region- and year fixed effects increases the plausibility of the effect being the wanted causal effect of private equity backing on industries. At most, we control for close to 6000 individual industry-region combinations, while at the same time considering yearly fixed effects. The great reduction in economic magnitude moving to the much stricter specifications could indicate that we have reduced causality concerns regarding the selection effect, as well as other non-private equity related factors. Moreover, the effects hold in significance independent of the industry classification. As discussed in chapter 6.2, GP's choice of industries to invest in should be increasingly random when considering very fine classifications of industries. Since it is still significant, it increases the plausibility that we have isolated the effect of private equity spillover effects. Finally, Bernstein, et al. (2017), also argue that their findings of significantly positive outperformance in favour of buyout industries should be attributed to spillovers, having run several tests for plausibly confirming causality.

In relation to the Wald test, the results invite several interpretations. It could suggest that industries with high buyout activity have the highest outperformance due to GPs selecting the industries with the best prospects. On the other hand, it could simply be that higher activity is a necessity for the spillovers to occur. A single buyout may create little awareness, while consecutive buyouts could arguably be hard to overlook. Finally, the outperformance could be largely due to the actual companies receiving backing. However, this argument should be weak, considering that these firms encompass a very small share of entire industries. If the selection effect was indeed the case in our findings, the relationship should be significant in favour of *BO High* regardless of the classification. Seeing that this is not the case for multiple metrics, this suggests that the effect is due to industry *spillovers* and not due to GPs selecting the most promising industries. This argument is further strengthened since buyouts are extremely dispersed among the different categories of the finest classification. Moving from coarse to finer classifications, we mostly see the differences between high- and low buyout activity disappear. As pointed out by Bernstein, et al. (2017), results should at least be partly driven by spillover effects when industries with high- and low buyout activity are similar. Considering that we find few differences when employing a comparatively much finer industry classification, suggests this statement to be true. If spillover effects were not present, one would expect industries with more private equity backed companies to have a higher outperformance. Hence, the evidence in support of H1 is even more prominent.

In order to provide additional robustness, all analyses explained in chapter 7.1 were repeated using the SN2002 industry codes as well as with a few variations of clustered standard errors. These approaches returned approximately the same results as the main analysis.

In conclusion, we have found clear evidence of outperformance of buyout industries, relative to non-buyout industries, and substantial indication that spillover effects contribute a significant share in said outperformance. With this in mind, we are curious to explore whether we are able to identify spillover effects in competitors' performance.

7.2 Impact of Buyouts on Competitors of Portfolio Companies

Having identified possible industry spillover effects, the proceeding subchapters investigate further whether these spillover effects can be identified in competitors of the portfolio companies backed by private equity. We will explore the impact of buyout activity on respectively operational- and financial performance, as well as distress risk. The main analysis employs the sample of 96 close- and distant competitors, as produced by PSM, explained in chapter 5.3. Next, the analysis is repeated using another model specification and then an alternative sample to provide robustness. Finally, we discuss the overall results and relate them to hypothesis three formulated in chapter 4.

7.2.1 Operational Performance

We begin by exploring whether we can identify any spillovers on close competitors' operational performance from companies receiving private equity backing. Table 6 contains regression analyses of close competitors' performance along the dimensions of total income, EBIT margin, FA ratio and asset turnover ratio. For each performance metric, three specifications are included, capturing the relative change from respectively year zero to one, zero to two and zero to three. Zero being the year of the buyout. Additionally, we impose clustered standard errors by company. This involves more than 160 clusters, which is much more than the rule of thumb of 42 suggested by Angrist and Pischke (2008, p. 238). Furthermore, adding the additional controls reduce the chances of omitted variable bias.

Table 6 paints an overall picture of insignificant relationships, indicating that close competitors of portfolio companies do not outperform distant competitors. In column (10) through (12), we see that Asset Turnover Ratio is significantly higher at the 5% level for close competitors than distant competitors at the time of buyout. Aside from this, no significant differences exist at the time of buyout. While the coefficients on DD_1, DD_2 and DD_3 are consistently positive for Total Income and FA Ratio, and consistently negative for EBIT margin and Asset Turnover Ratio, the relationships are far from significant. Since we have established strong indications of spillover effects within industries experiencing buyouts, but are unable to detect differences in operational performance between close- and distant competitors, this suggests that the observed effect is likely an industry wide effect, supporting H3b.

In Table B9, we expand all 12 models in Table 6 with controls for industry fixed effects. The finest classification is employed, since it was applied in PSM and captures the most representative industry characteristics. Nonetheless, no noteworthy changes materialise.

Overall, results in table 6 leaves us unable to infer that private equity-backed companies create positive spillovers for close competitors' operational performance, hence providing evidence that H3a may be false. However, we do note that we may be unable to detect significant relationships due to lack of statistical power.

Table 6. Impact of Buyout Activity on Competitors' Operational Performance

The table consists of coefficient estimates of OLS panel data regressions of respectively Total Income, EBIT Margin, FA Ratio and Asset Turnover to Assets on PE ownership. Total Income is simply the natural logarithm of total income. EBIT margin is sourced from SNF and is defined as EBIT to total income. FA ratio is defined as the sum of real property, machinery and plant and ships, rigs, planes, etc. to total assets. Asset Turnover Ratio is defined as total income to total assets. The sample initially consist of 96 pairs of close- and distant competitors, but may vary depending on the numbers of existing values of the performance measure being used. Comptype is equal one if the company is a close competitor and zero if the company is a distant competitor. $Dyear_1$, $Dyear_2$ and $Dyear_3$ are equal to one if the year is respectively one, two or three years post buyout and zero at the year of buyout. DD_1, DD_2 and DD3 are the measures of interest and contain the difference-in-differences effects. They are the products of comptype and respectively $Dyear_1$, $Dyear_2$ and $Dyear_3$. The specifications implement difference-in-differences estimation. See Appendix A for descriptions of all variables. Standard errors are clustered by individual company and in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1) Total Income	(2) Total Income	(3) Total Income	(4) EBIT Margin	(5) EBIT Margin	(6) EBIT Margin	(7) FA Ratio	(8) FA Ratio	(9) FA Ratio	(10) Asset Turnover Ratio	(11) Asset Turnover Ratio	(12) Asset Turnover Ratio
Comptype	-0.34	-0.34	-0.35	0.20	0.20	0.19	0.00	0.00	0.00	0.30**	0.30**	0.30**
	(0.32)	(0.31)	(0.31)	(0.26)	(0.25)	(0.25)	(0.03)	(0.03)	(0.03)	(0.15)	(0.15)	(0.15)
$Dyear_1$	-0.20			-0.04			-0.00			-0.04		
	(0.17)			(0.21)			(0.00)			(0.05)		
DD_1	0.24			-0.03			0.01			-0.04		
	(0.19)			(0.26)			(0.01)			(0.10)		
$Dyear_2$		-0.21			0.29			-0.02*			-0.02	
		(0.19)			(0.25)			(0.01)			(0.07)	
DD_2		0.12			-0.36			0.02			-0.12	
		(0.25)			(0.31)			(0.01)			(0.11)	
$Dyear_3$			-0.43**			-0.09			-0.02**			0.00
			(0.22)			(0.23)			(0.01)			(0.08)
DD_3			0.44			-0.06			0.01			-0.10
			(0.29)			(0.32)			(0.01)			(0.14)
Constant	11.29***	11.31***	11.32***	-0.33	-0.32	-0.31	0.10***	0.10***	0.10***	0.41***	0.41***	0.40***
	(0.21)	(0.21)	(0.21)	(0.22)	(0.22)	(0.22)	(0.02)	(0.02)	(0.02)	(0.10)	(0.10)	(0.10)
N	357	360	355	358	360	355	361	368	369	361	368	369
R2	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.02	0.01

7.2.2 Financial Performance

Next, we proceed to investigate financial performance. Table 7 displays regression analyses for close competitors' ROE, ROA and FCF to (total) Assets. The specifications follow the same structure as in the preceding subchapter.

Comptype is consistently positive for ROE and ROA, while it is consistently negative for FCF to Assets. However, it is insignificant in all specifications, meaning close- and distant competitors were not different at the time of buyout in terms of ROE, ROA and FCF to Assets. Interestingly, the coefficient on DD_3 is positive and significant at the 10% level for ROE, providing weak evidence of possible spillover effects onto close competitors' financial

Table 7. Impact of Buyout Activity on Competitors' Financial Performance

The table consists of coefficient estimates of OLS panel data regressions of respectively ROE, ROA and FCF to Assets on PE ownership. The specifications implement difference-in-differences estimation. ROE is defined as net income to equity, ROA as net income to total assets and FCF to Assets as the sum of EBIT and depreciation and amortisation, less net working capital and capital expenditures to total assets. The sample initially consist of 96 pairs of close- and distant competitors, but may vary depending on the numbers of existing values of the performance measure being used. See Table 6. for descriptions of all variables. Standard errors are clustered by individual company and in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1) ROE	(2) ROE	(3) ROE	(4) ROA	(5) ROA	(6) ROA	(7) FCF to Assets	(8) FCF to Assets	(9) FCF to Assets
Comptype	-0.76	-0.75	-0.74	-0.36	-0.35	-0.35	0.08	0.07	0.07
	(0.61)	(0.61)	(0.60)	(0.29)	(0.29)	(0.29)	(0.12)	(0.11)	(0.11)
$Dyear_1$	-0.81			-0.02			-0.01		
	(0.59)			(0.01)			(0.03)		
DD_1	0.38			0.30			-0.12		
	(0.71)			(0.29)			(0.11)		
$Dyear_2$		-0.76			-0.02			-0.00	
		(0.59)			(0.02)			(0.03)	
DD_2		0.55			0.33			-0.08	
		(0.61)			(0.28)			(0.12)	
$Dyear_3$			-0.78			-0.03*			0.01
			(0.58)			(0.01)			(0.03)
DD_3			1.45*			0.25			-0.13
			(0.74)			(0.28)			(0.11)
Constant	0.94	0.93	0.92	0.05***	0.05***	0.05***	0.07***	0.07***	0.07***
	(0.61)	(0.60)	(0.59)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
N	361	368	368	361	368	369	353	360	361
R2	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.00	0.00

performance. This could suggest that close competitors in the long run increase their net income, reduce their equity or do both. Additionally, coefficients for DD_1 and DD_2 are also positive, but stay insignificant. Table B10 adds industry fixed effects to the model. Results are almost identical, with DD_3 for ROE in column (3) turning insignificant being a change worth mentioning.

Table 8. Impact of Buyout Activity on Competitors' Distress Risk

The table consists of coefficient estimates of OLS panel data regressions of respectively Leverage Ratio and Interest Coverage Ratio. The specifications implement difference-in-differences estimation. Leverage Ratio is defined as total debt to total assets and Interest Coverage Ratio as EBIT to interest expenses. The sample initially consist of 96 pairs of close- and distant competitors, but may vary depending on the numbers of existing values of the performance measure being used. See Table 6. for descriptions of all variables. Standard errors are clustered by individual company and in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1) Leverage Ratio	(2) Leverage Ratio	(3) Leverage Ratio	(4) Interest Coverage Ratio	(5) Interest Coverage Ratio	(6) Interest Coverage Ratio
Comptype	2.04	2.00	2.00	517.65**	510.05**	510.05**
	(1.36)	(1.33)	(1.33)	(225.43)	(222.20)	(222.22)
$Dyear_1$	-0.03**			-31.03		
	(0.01)			(45.44)		
DD_1	-1.07			-7.80		
	(1.30)			(319.19)		
$Dyear_2$		-0.01			42.37	
		(0.03)			(68.73)	
DD_2		-1.41			-217.24	
		(1.26)			(378.55)	
$Dyear_3$			-0.04			25.45
			(0.03)			(92.76)
DD_3			0.60			-40.70
			(2.28)			(479.69)
Constant	0.62***	0.61***	0.61***	-32.03	-31.33	-31.33
	(0.02)	(0.02)	(0.02)	(111.08)	(109.04)	(109.05)
N	361	368	369	242	249	247
R2	0.01	0.01	0.01	0.03	0.02	0.01

7.2.3 Distress Risk

Thus far, we have looked at the operational and financial performance of close competitors, mostly finding no noteworthy differences. We now turn to inspecting the distress risk of the close competitors. Table 8 presents regression analyses for two performance metrics related to distress risk, namely Leverage Ratio and Interest Coverage Ratio. Again, the specifications follow the same structure as in the two preceding subchapters.

If taken at face value, column (1) and (2) implies that close competitors relative to distant competitors, reduce their leverage following the buyout of their competitor, i.e. the portfolio company. Again, no significance exist and we are thus unable to make statistical inference. The Interest Coverage Ratio is found to be significantly higher for close competitors in the buyout year, but no statistical evidence of spillovers exist. Furthermore, the coefficients are spurious due to extreme outliers. When we extend the model with industry fixed effects the results remain similar, aside from *Comptype* losing moderate significance.

7.2.4 Further Discussion

In this section, we first view our findings in light of both parts of H3 and then discuss the implications of these findings. The way we specify PSM in chapter 5.3 allows us to relate the analysis of competitors back to the industry analysis and explore whether close competitors also drive the outperformance for buyout industries or if it is industry wide. The overwhelming majority of results provide no support of H3a, instead suggesting that the effect is an industry wide effect, in support of H3b. More specifically, we find no statistical basis to infer spillover effects mainly on close competitors of portfolio companies backed by private equity, implying the spillovers mainly be industry wide.

However, we do note that other possible interpretations exist. One alternative interpretation could be that the portfolio companies themselves drive the outperformance. This appears unlikely, considering their incredibly small share compared to the industry as a whole. Furthermore, when employing the finest classification, the buyout transactions are highly dispersed, with fewer transactions occurring in the same specific subindustry. It seems far-fetched to claim that single companies in many cases drive the outperformance of the entire industry. Considering approximately all relationships in chapter 7.1 hold in significance when employing increasingly detailed industry classifications, it suggests that portfolio companies driving industry outperformance is not the case. A third interpretation, which is practically a continuation of the first one, could be that spillover effects influence both the close- *and* distant competitors in our given sample. In consequence, this yield insignificant differences. This would support the effect as an industry wide effect. In conclusion, the effect thus seems to be industry wide.

Insignificant relationships may also arise from a lack of statistical power, meaning that there *could* indeed be an effect, which we are unable to detect. We therefore repeat the analysis with the coarsest industry classification, allowing for a sample of 143 pairs of close- and distant competitors. This analysis yields largely the same results with the major difference between the analyses being that *Comptype* turns significant for many specifications when employing the coarsest classification. On the other hand, *it is* the *coarsest* classification and, as discussed in chapter 5.3, the matches are thus less likely to in fact be close competitors. An increase in significant relationships could signify that lack of power may be of importance in our case. Furthermore, the lack of significance for the difference-in-differences variable could be due to the fact that the sample based on the coarsest classification likely does not paint a true picture of what are close and what are distant competitors. As discussed, one could end up with very unrepresentative matches using such broad classifications.

Aldatmaz and Brown (2018) state that spillovers onto competing companies exist due competitive pressure from private equity backed firms, since they find the positive effect of private equity to be concentrated in industries with higher levels of competition. Harford, et al. (2016) support the notion that spillovers to companies in the same industry as the buyout occurs, are due to the competition intensifying. Nonetheless, we are unable to find significant evidence suggesting spillovers to exist for mainly the close competitors.

Overall, the results yield few significant relationships, but the implications are still an important contribution to the literature. To be more precise, the results from this chapter, in relation to the results of the industry analysis, raise implications that spillover effects from private equity backing are industry wide.

8. Limitations

As a final remark before providing a conclusion, we touch upon certain limitations to this thesis. First, since we have fewer than optimal observations of private equity transactions, the analyses may lack statistical power in determining the relationships. Said differently, there possibly exist spillover effects to close competitors that we are unable to detect given the sample. Furthermore, one needs to acknowledge that there is no perfect correlation between accounting performance and actual performance.

The dataset consists of accounting data that report financial measures at end of the fiscal year, i.e. 31.12. Considering that we have to rely on the year of the buyout when finding matches, since accounting data are often missing prior to the buyout, a troublesome scenario may arise. The year of the buyout is the base year for the analysis, i.e. t=0, meaning that if the buyout took place at the beginning of the year, some of the private equity effect may have already occurred. However, it is reasonable to assume that limited effect takes place in the same year as the buyout, especially when one considers time-consuming transfers of ownership as well as implemented changes requiring time to yield gains.

It is plausible that the sample produced by PSM could be somewhat unrepresentative for close- or distant competitors or both. We design and impose the criteria deemed relevant in selecting buyout targets, on which PSM will run the matching algorithm, and based on this, PSM returns the resulting pairs of close- and distant competitors. It could thus be that the pairs are unrepresentative. While it would indeed be optimal to interview the CEOs of companies and question them who their closest- and distant competitors are or studying all annual reports for portfolio companies, we will have to settle for one of the next best options.

Companies receiving private equity backing might change their operations, resulting in their given main industry classification changing after some time. In other words, if a company is under private equity management for five years, it may be categorised as one specific industry the first couple of years and a different industry for the remainder. For the purpose of this thesis, we have applied the industry in which the buyout first occurred. Finally, the issues regarding the direction of causality could still prevail, despite our efforts in accounting for it. As previously discussed, this is a common problem in private equity research, and one that is often difficult to fully account for.

9. Conclusion and Implications for Further Research

This thesis examines spillover effects from private equity to industries and close competitors of portfolio companies backed by private equity. Using a unique sample that includes all private Norwegian companies as well as multiple industry classifications of varying detail, we explore the impact of 192 buyouts. This allow us to examine effects on whole industries and it also has important implications for better isolation of spillover effects.

We find that industries experiencing buyout activity outperform industries that do not experience buyout activity. In support of the observed effect being due to spillovers, the findings are highly robust to increasingly detailed industry classifications and controls. The initial analysis finds that industries with high buyout activity outperform industries with lower levels of buyout activity, but the effect disappears when employing the finest industry classification. This further supports the notion of spillover effects. Rooted in the industry analysis, we then analyse the impact on close competitors, finding no evidence of spillovers to individual competitors, suggesting that the spillovers are industry wide.

This thesis contributes new evidence to the field by using an innovative approach to identifying causal effects and goes beyond the usual research suspects in private equity, thus exploring less researched questions. The findings are highly relevant in assessing private equity as a whole and hence important for policymakers. Having provided evidence against the common view that private equity destroys value, we hope that we have cleared some of the air around the misunderstandings and negative labelling of private equity.

We see several great opportunities for further research in relation to private equity and also this thesis. Had it not been outside the scope and time restriction of this thesis, it would be highly interesting to explore the impact of private equity investment on the export performance of Norwegian companies, as an extension of this thesis. This topic is of importance, since it is one of the main components comprising GDP, and the case of Norway is especially interesting, since it is a small and open economy, strongly dependent on its export. Such a paper could be accomplished by accessing data from the Norwegian Tax Administration on revenue flows going abroad and combining this data with the ACPE and SNF databases.

Additionally, a similar paper focusing on the effects on competitors where one can achieve higher statistical power is encouraged. Moreover, identifying competitors along some other measure, such as the fluidity measure, or as mentioned in chapter 8, by interviewing CEOs or studying annual reports, could yield welcoming results. Finally, we encourage future research that sheds light on *how* each individual industry and/or company is impacted by private equity. In other words, through what channels the industries and companies are affected.

10. References

Abadie, A. & Imbens, G. W., (2006). Large Sample Properties of Matching Estimators for Average Treatment Effects. *Econometrica Vol. 74 (1)*, pp. 235-267.

Aldatmaz, S. & Brown, G. W., (2018). Private Equity in the Global Economy: Evidence on Industry Spillovers. *UNC Kenan-Flagler Research Paper No. 2013-9; 29th Annual Conference on Financial Economics & Accounting 2018*.

Angrist, J. D. & Jörn-Steffen, P., (2008). *Mostly Harmless Econometrics: An Empiricist's Companion.* New Jesey, US.:Princeton University Press.

Angrist, J. D. & Pischke, J.-S., (2015). *Mastering Metrics: The Path from Cause to Effect.* Princeton, New Jersey, US: Princeton University Press.

Argentum, (2012). *Annual Report 2012*, Argentum.

Argentum, n.d. *Argentum Portfolio.* [Online]
Available at: https://argentum.no/en/portfolio/
[Accessed 27. November 2018].

Berner, E., Mjøs, A. & Olving, M., (2016). *Norwegian Corporate Accounts: Documentation and quality assurance of SNF's and NHH's database of accounting and company information for Norwegian companies*, Bergen: Centre for Applied Research at NHH.

Bernstein, J. & Nadiri, I. M., (1989). Research and Development and Intra-industry Spillovers: An Empirical Application of Dynamic Duality. *Review of Economic studies Vol. 56 (2)*, pp. 249-267.

Bernstein, S., Lerner, J., Sorensen, M. & Strömber, P., (2010). Private Equity and Industry Performance. *Working Paper, National Bureau of Economic Research*.

Bernstein, S., Lerner, J., Sorensen, M. & Strömber, P., (2014). Private Equity and Industry Performance. *Netspar Discussion Papers*.

Bernstein, S., Lerner, J., Sorensen, M. & Strömber, P., (2017). Private Equity and Industry Performance. *Management Science 63(4)*, pp. 1198-1213.

Bernstein, S. & Sheen, A., (2016). The Operational Consequences of Private Equity Buyouts: Evidence from the Restaurant Industry. *The Review of Financial Studies Vol 29 (9)*, pp. 2387-2418.

Bienz, C., (2016a). Leveraged Buyouts in Norway. *Argentum Centre for Private Equity, Publications and Current Projects*.

Bienz, C., Thorburn, K. S. & Walz, U., (2016b). Co-investment and risk taking in private equity funds. *SAFE Research Center Working Paper Series 126, University of Frankfurt*.

Blomström, M. & Kokko, A., (1998). Multinational Corporations and Spillovers. *Journal of Economic Surveys Vol 12 (3)*, pp. 247-277.

Bloomberg, (2018). *Norway Once Again Rejects Private Equity for $1 Trillion Fund,* Bloomberg.

Bloom, N., Sadun, R. & Van Reenen, J., (2015). Do Private Equity Owned Firms Have Better Management Practices?. *The American Economic Review, Vol. 105, No. 5*, pp. 442-446.

Brown, G. & Witte, P., (2018). *Unerstanding PE's Impact on the Economy,* EY and the Institute for Private Equity.

Caliendo, M. & Kopeinig, S., (2008). Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Surveys*, pp. 31-72.

Caves, R. E., (1974). Multinational Firms, Competition, and Productivity in Host-country Markets. *Economica Vol 41 (162)*, pp. 176-193.

Cendrowski, H., Petro, L. W., Marin, J. P. & Wadecki, A. A., (2012). *Private Equity: History, Governance, and Operations.* 2. ed. New Jersey:John Wiley & Sons, Inc.

Chevalier, J. A., (1995). Capital Structure and Product-market Competition: Empirical Evidence from the Supermarket Industry. *The American Economic Review Vol 85 (3)*, pp. 415-435.

Cumming, D., (2010). *Private Equity: Fund Types, Risks and Returns, and Regulation.* Hoboken, New Jesey:John Wiley & Sons, Inc.

Davis, S. J. et al., (2014). Private Equity, Jobs, and Productivity. *Chicago Booth Research Paper No. 14-16*.

Fonseka, M. M., Theja N. Rajapakse, R. L. & Tian, G.-L., (2018). Competitors' Stock Price Reactions in Response to Private Equity Placements: Evidence from a Transitional Economy. *Economic Research - Ekonomska Istrazivanja 31:1*.

Fraser-Sampson, G., (2010). *Private Equity as an Asset Class.* 2. ed. West Sussex, United Kingdom:John Wiley & Wiley.

Gertler, P. J. et al., (2011). *Impact Evaluation in Practice.* 1. ed. Washington DC: The World Bank.

Hammerich, P. & Heistad, M., (2018). *The Private Equity Review: (II) Investments - Chapter 13, Norway*, London, UK.: The Law Reviews.

Harford, J., Stanfield, J. R. & Zhang, F., (2016). How Does an LBO Impact the Target's Industry?. *Working Paper*.

Invest Europe, (2018). *European Private Equity Report 2017: Statistics on Fundraising, Investments & Divestments,* Invest Europe.

Invest Europe, n.d. *About Private Equity.* [Online]
Available at: https://www.investeurope.eu/about-private-equity/private-equity-explained/?fbclid=IwAR1PunFRWU5rqJvOuE7YJxALuGeooZb_ldNXGCgGyaXKAHkImLS_GIu5PNE
[Accessed November 2018].

Investopedia, n.d. *Mezzanine Debt.* [Online]
Available at: https://www.investopedia.com/terms/m/mezzaninedebt.asp
[Accessed 14 December 2018].

Jensen, M. C., (1989). Eclipse of the Public Corporation. *Harvard Business Review 67*, pp. 61-74.

Kaplan, S., (1989). The Effects of Management Buyouts on Operating Performance and Value. *Journal of Financial Economics*, pp. 217-254.

Kaplan, S. N. & Strömberg, P., (2009). Leveraged Buyouts and Private Equity. *Journal of Economic Perspectives—Volume 23, Number 1,* pp. 121-146.

Lechner, M., (2010). The Estimation of Causal Effects by Difference-in-Difference Methods. *Foundations and Trends in Econometrics Vol. 4, No. 3,* pp. 165-224.

Lerner, J. & Schoar, A., (2005). Does Legal Enforcement Affect Financial Transactions?The Contractual Channel in Private Equity. *The Quarterly Journal of Economics vol. 120, issue 1,* pp. 223-246.

Lerner, J., Sorensen, M. & Strömberg, P., (2011). Private Equity and Long-Run Investment: The Case of Innovation. *The Journal of Finance, Vol. 66(2),* pp. 445-477.

Menon Economics, (2018). *Private Equity Funds in Norway,* Menon Economics.

Metrick, A. & Yasuda, A., (2010). *Venture Capital and the Finance of Innovation.* 2. ed. New Jersey: John Wiley & Sons, Inc.

NBIM, n.d. *Homepage: Norges Bank Investment Management.* [Online]
Available at: https://www.nbim.no/
[Accessed 27. November 2018].

Oxman, J. & Yildirim, Y., (2008). Governance Effects of LBO Events. *Working Paper Syracuse University*.

Preqin, (2015). Buyout Holding Periods. *Private Equity Spotlight vol. 11(4),* p. 7.

PricewaterhouseCoopers (PwC), (2018). *Private Equity Trend Report: the Coming of Age,* PricewaterhouseCoopers

Rosenbaum, P. R. & Rubin, D. B., (1983). The Central Role of Propensity Score in Observational Studies for Causal Effects. *Biometrika Vol. 70 (1),* pp. 41-55.

Syrstad, R. S. & Grimsby, G., (2017). *Value Creation analysis for Private Equity Funds in Norway,* Menon Economics.

Verdane Capital, n.d. *About Verdane.* [Online]
Available at: https://www.verdane.com/category/3
[Accessed 27. November 2018].

Wiese-Hansen, K. H. & Nordal, S., (2018). *The Private Equity Review: (I) Fundraising - Norway*, pp. 156-165. London, UK: The Law Reviews.

Wooldridge, J. M., (2013). *Introductory Econometrics: A Modern Approach.* 5. ed. Mason, OH: Cengage Learning.

11. Appendices

11.1 Appendix A – Description of Variables

Table A1. Variable Description

Panel A: Performance metrics used as dependent variables	
Asset Turnover Ratio	Total income to total assets.
FA Ratio	Fixed/real assets to total assets. Fixed assets is defined as the sum of real property, machinery and plant, and ships, rigs, planes, etc.
FCF/Assets	Natural logarithm of free cash flow to total assets. Free cash flow is defined as the sum of EBIT, depreciation and amortisation, less net working capital and capital expenditures. Net working capital is defined as the difference between current assets and current liabilities.
Fixed Capital Growth	Natural logarithm of fixed/real capital, defined as the sum of real property, machinery and plant, and ships, rigs, planes, etc.
Interest Coverage Ratio	EBIT to interest expenses
Leverage Ratio	Total debt to total assets
Number of Companies	Natural logarithm of the total number of companies
Total Output	Natural logarithm of the sum of total income and stocks at the end of the year, less stocks at the beginning of year
EBIT Margin	EBIT to total income.
ROA	Return on Assets. Measured as net income to total assets
ROE	Return on Equity. Measured as net income to equity
Total Income	Natural logarithm of total income
Value Added	Natural logarithm of total output (see above) less cost of raw materials and consumables

Panel B follows on the next page

Panel B: Covariates used as controls in PSM and analyses	
BO High	Indicator variable that equals 1 if the industry has high buyout activity, defined as being above the average number of buyouts across industries.
BO Low	Indicator variable that equals 1 if the industry has low buyout activity, defined as being below the average number of buyouts across industries.
BO Industry	Indicator variable that equals 1 if the industry is a buyout industry, defined as the industry having experienced at least one buyout in the last five years.
Comptype	Indicator variable that equals one if the competitor is a close competitor, zero if it is a distant competitor.
$Dyear_1$	Indicator variable equal one if the year is one year post buyout, zero if the year is the buyout year
$Dyear_2$	Indicator variable equal one if the year is two years post buyout, zero if the year is the buyout year
$Dyear_3$	Indicator variable equal one if the year is three years post buyout, zero if the year is the buyout year
DD_1	Difference-in-differences term. Cross product of $Dyear_1$ and Comptype
DD_2	Difference-in-differences term. Cross product of $Dyear_2$ and Comptype
DD_3	Difference-in-differences term. Cross product of $Dyear_3$ and Comptype
lev	Leverage degree. Defined as total debt to equity
likv	Liquidity ratio. Defined as current assets to current liabilities
lnsize	Proxy for size of company. Natural logarithm of total assets.
Industry FE	Set of N-1 dummy variables, capturing industry specific effects for each individual industry, equal to one if the industry is industry *i*.
Year FE	Set of N-1 dummy variables, capturing year specific effects for each of the 24 years, equal to one if the year is year j.
Industry-Region FE	Set of N-1 dummy variables, defined as the cross product of the region variable (ranging from 1-7) and the industry variable (14, 87 or 799 distinct five digit codes, depending on which industry classification being used). It equals one if the industry is industry *i* and the region is region *r*.
Industry-Year FE	Set of N-1 dummy variables, defined as the cross product of the year variable (ranging from 1992-2015) and the industry variable (14, 87 or 799 distinct five digit codes, depending on which industry classification being used). It equals one if the industry is industry *i* and the year is year *j*.

11.2 Appendix B – Output of Additional Analyses

Table B1. Impact of Buyout Activity on Total Industry Output Using the *Second Finest* Industry Classification

The table presents coefficient estimates of OLS panel data regressions of total output on PE ownership. An observation is an industry-region-year combination, using the second finest industry classification of 87 industry categories, 7 region categories and 24 separate years. Total Output is defined as the sum of total income and change in inventory of goods. BO Industry is equal one if the industry is a buyout industry, while BO High and BO Low are equal one if the industry is a buyout industry and is respectively above or below the mean number of buyouts per industry. Fixed effects for the products of industry-year and industry-region are also included. Finally, $BO_H = BO_L$ is a Wald test for equality. See Appendix A for descriptions of all variables. Standard errors are heteroskedasticity-robust and in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1) Total Output	(2) Total Output	(3) Total Output	(4) Total Output	(5) Total Output	(6) Total Output
BO Industry	2.22***	1.89***	0.45***			
	(0.08)	(0.08)	(0.06)			
BO High				2.28***	2.17***	0.66***
				(0.12)	(0.13)	(0.10)
BO Low				2.15***	1.56***	0.23***
				(0.10)	(0.08)	(0.07)
Constant	10.44***	13.23***	11.15***	10.44***	13.23***	11.15***
	(0.51)	(0.23)	(0.75)	(0.51)	(0.23)	(0.75)
Industry-Year FE	X		X	X		X
Industry-Region FE		X	X		X	X
$BO_H = BO_L$				0.41	0.00***	0.00***
N	13,052	12,645	12,645	13,052	12,645	12,645
R2	0.53	0.45	0.84	0.53	0.45	0.84

Table B2. Impact of Buyout Activity on Industry Value Added Using the *Second Finest* Industry Classification

The table presents coefficient estimates of OLS panel data regressions of value added on PE ownership. An observation is an industry-region-year combination, using the second finest industry classification of 87 industry categories, 7 region categories and 24 separate years. Value added is defined as the sum of total income and change in inventory of goods less cost of goods sold. The remaining variables are defined in Table B1. Standard errors are heteroskedasticity-robust and in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1) Value Added	(2) Value Added	(3) Value Added	(4) Value Added	(5) Value Added	(6) Value Added
BO Industry	2.23***	1.82***	0.45***			
	(0.07)	(0.08)	(0.05)			
BO High				2.30***	2.13***	0.66***
				(0.10)	(0.12)	(0.08)
BO Low				2.13***	1.47***	0.24***
				(0.10)	(0.08)	(0.07)
Constant	11.22	12.63***	10.82***	11.22***	12.63***	10.82***
	(.)	(0.25)	(0.11)	(0.00)	(0.25)	(0.11)
Industry-Year FE	X		X	X		X
Industry-Region FE		X	X		X	X
$BO_H = BO_L$				0.25	0.00***	0.00***
N	12,969	12,569	12,569	12,969	12,569	12,569
R2	0.52	0.45	0.85	0.52	0.45	0.85

Table B3. Impact of Buyout Activity on Industry Fixed Capital Growth Using the *Second Finest* Industry Classification

The table displays coefficient estimates of OLS panel data regressions of fixed capital growth on PE ownership. An observation is an industry-region-year combination, using the second finest industry classification of 87 industry categories, 7 region categories and 24 separate years. Fixed capital growth is the natural logarithm of the sum of real property, machinery and plant, and ships, rigs, planes, etc. The remaining variables are explained in Table B1. Standard errors are heteroskedasticity-robust and in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1) Fixed Capital	(2) Fixed Capital	(3) Fixed Capital	(4) Fixed Capital	(5) Fixed Capital	(6) Fixed Capital
BO Industry	2.05***	1.59***	0.40***			
	(0.08)	(0.09)	(0.07)			
BO High				2.20***	1.76***	0.60***
				(0.13)	(0.14)	(0.12)
BO Low				1.87***	1.39***	0.19**
				(0.10)	(0.10)	(0.08)
Constant	9.49***	11.83***	10.54***	9.49***	11.83***	10.54***
	(0.63)	(0.20)	(0.29)	(0.63)	(0.20)	(0.29)
Industry-Year FE	X		X	X		X
Industry-Region FE		X	X		X	X
$BO_H = BO_L$				0.05*	0.03**	0.00***
N	12,785	12,442	12,442	12,785	12,442	12,442
R2	0.58	0.47	0.84	0.58	0.47	0.84

Table B4. Impact of Buyout Activity on Number of Companies per Industry Using the *Second Finest* Industry Classification

The table displays coefficient estimates of OLS panel data regressions of number of companies on PE ownership. An observation is an industry-region-year combination, using the second finest industry classification of 87 industry categories, 7 region categories and 24 separate years. Number of companies is defined as the natural logarithm of the number of companies. The remaining variables are explained in Table B1. Standard errors are heteroskedasticity-robust and in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1) Number of Companies	(2) Number of Companies	(3) Number of Companies	(4) Number of Companies	(5) Number of Companies	(6) Number of Companies
BO Industry	1.50***	1.04***	0.33***			
	(0.05)	(0.05)	(0.03)			
BO High				1.60***	1.18***	0.51***
				(0.06)	(0.07)	(0.05)
BO Low				1.38***	0.87***	0.15***
				(0.06)	(0.06)	(0.04)
Constant	2.56***	4.11***	2.88***	2.56***	4.11***	2.88***
	(0.43)	(0.16)	(0.18)	(0.43)	(0.16)	(0.18)
Industry-Year FE	X		X	X		X
Industry-Region FE		X	X		X	X
$BO_H = BO_L$				0.01**	0.00***	0.00***
N	13,455	12,914	12,914	13,455	12,914	12,914
R2	0.72	0.57	0.95	0.72	0.57	0.95

Table B5. Impact of Buyout Activity on Total Industry Output Using the *Finest* Industry Classification

The table presents coefficient estimates of OLS panel data regressions of total output on PE ownership. An observation is an industry-region-year combination, using the finest industry classification of 799 industry categories, 7 region categories and 24 separate years. Total Output is defined as the sum of total income and change in inventory of goods. The remaining variables are defined in Table B1. Standard errors are heteroskedasticity-robust and in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1) Total Output	(2) Total Output	(3) Total Output	(4) Total Output	(5) Total Output	(6) Total Output
BO Industry	3.69***	0.76***	0.17***			
	(0.07)	(0.04)	(0.03)			
BO High				4.03***	0.75***	0.07*
				(0.10)	(0.05)	(0.04)
BO Low				3.37***	0.76***	0.26***
				(0.11)	(0.06)	(0.05)
Constant	21.06	10.48***	8.73***	21.06	10.48***	8.73***
	(.)	(0.15)	(0.05)	(.)	(0.15)	(0.05)
Year FE	X		X	X		X
Industry-Region FE		X	X		X	X
BOH = BOL				0.00***	0.97	0.00***
N	87,228	85,775	85,775	87,228	85,775	85,775
R2	0.04	0.78	0.85	0.04	0.78	0.85

Table B6. Impact of Buyout Activity on Industry Value Added Using the *Finest* Industry Classification

The table presents coefficient estimates of OLS panel data regressions of value added on PE ownership. An observation is an industry-region-year combination, using the finest industry classification of 799 industry categories, 7 region categories and 24 separate years. Value added is defined as the sum of total income and change in inventory of goods less cost of goods sold. The remaining variables are defined in Table B1. Standard errors are heteroskedasticity-robust and in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1) Value Added	(2) Value Added	(3) Value Added	(4) Value Added	(5) Value Added	(6) Value Added
BO Industry	3.61***	0.78***	0.20***			
	(0.07)	(0.04)	(0.03)			
BO High				4.04***	0.81***	0.13***
				(0.09)	(0.05)	(0.03)
BO Low				3.22***	0.76***	0.27***
				(0.10)	(0.06)	(0.05)
Constant	20.52***	9.88***	8.16***	20.52***	9.88***	8.16***
	(0.00)	(0.16)	(0.06)	(0.00)	(0.16)	(0.06)
Year FE	X		X	X		X
Industry-Region FE		X	X		X	X
$BO_H = BO_L$				0.00***	0.54	0.02**
N	86,421	85,009	85,009	86,421	85,009	85,009
R2	0.05	0.77	0.85	0.05	0.77	0.85

Table B7. Impact of Buyout Activity on Industry Fixed Capital Growth Using the *Finest* Industry Classification

The table displays coefficient estimates of OLS panel data regressions of fixed capital growth on PE ownership. An observation is an industry-region-year combination, using the finest industry classification of 799 industry categories, 7 region categories and 24 separate years. Fixed capital growth is the natural logarithm of the sum of real property, machinery and plant, and ships, rigs, planes, etc. The remaining variables are explained in Table B1. Standard errors are heteroskedasticity-robust and in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1) Fixed Capital	(2) Fixed Capital	(3) Fixed Capital	(4) Fixed Capital	(5) Fixed Capital	(6) Fixed Capital
BO Industry	2.77^{***}	0.52^{***}	0.14^{**}			
	(0.11)	(0.06)	(0.05)			
BO High				3.16^{***}	0.60^{***}	0.15^{**}
				(0.15)	(0.07)	(0.07)
BO Low				2.41^{***}	0.44^{***}	0.12
				(0.16)	(0.09)	(0.08)
Constant	20.15^{***}	9.71^{***}	8.64^{***}	20.15	9.71^{***}	8.64^{***}
	(0.00)	(0.18)	(0.12)	(.)	(0.18)	(0.12)
Year FE	X		X	X		X
Industry-Region FE		X	X		X	X
$BO_H = BO_L$				0.00^{***}	0.16	0.77
N	74,107	73,117	73,117	74,107	73,117	73,117
R2	0.04	0.76	0.79	0.04	0.76	0.79

Table B8. Impact of Buyout Activity on Number of Companies per Industry Using the *Finest* Industry Classification

The table displays coefficient estimates of OLS panel data regressions of number of companies on PE ownership. An observation is an industry-region-year combination, using the finest industry classification of 799 industry categories, 7 region categories and 24 separate years. Number of companies is defined as the natural logarithm of the number of companies. The remaining variables are explained in Table B1. Standard errors are heteroskedasticity-robust and in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1) Number of Companies	(2) Number of Companies	(3) Number of Companies	(4) Number of Companies	(5) Number of Companies	(6) Number of Companies
BO Industry	2.28***	0.48***	0.10***			
	(0.08)	(0.03)	(0.02)			
BO High				2.71***	0.56***	0.10***
				(0.08)	(0.04)	(0.02)
BO Low				1.88***	0.42***	0.09***
				(0.12)	(0.04)	(0.03)
Constant	11.39***	1.66***	0.83***	11.39***	1.66***	0.83***
	(0.00)	(0.24)	(0.15)	(0.00)	(0.24)	(0.15)
Year FE	X		X	X		X
Industry-Region FE		X	X		X	X
$BO_H = BO_L$				0.00***	0.01**	0.79
N	91,499	89,408	89,408	91,499	89,408	89,408
R2	0.05	0.83	0.91	0.05	0.83	0.91

Table B9. Impact of Buyout Activity on Competitors' Operational Performance with Industry Fixed Effects

The table consists of coefficient estimates of OLS panel data regressions of respectively Total Income, EBIT Margin, FA Ratio and Asset Turnover to Assets on PE ownership. Total Income is simply the natural logarithm of total income. EBIT margin is sourced from SNF and is defined as EBIT to total income. FA ratio is defined as the sum of real property, machinery and plant and ships, rigs, planes, etc. to total assets. Asset Turnover Ratio is defined as total income to total assets. The sample initially consist of 96 pairs of close- and distant competitors, but may vary depending on the numbers of existing values of the performance measure being used. Comptype is equal one if the company is a close competitor and zero if the company is a distant competitor. $Dyear_1$, $Dyear_2$ and $Dyear_3$ are equal to one if the year is respectively one, two or three years post buyout and zero at the year of buyout. DD_1, DD_2 and DD_3 are the measures of interest and contain the difference-in-differences effects. They are the products of comptype and respectively $Dyear_1$, $Dyear_2$ and $Dyear_3$. The specifications implement difference-in-differences estimation. Finally, all models include industry fixed effects using the finest classification. See Appendix A for descriptions of all variables. Standard errors are clustered by individual company and in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1) Total Income	(2) Total Income	(3) Total Income	(4) EBIT Margin	(5) EBIT Margin	(6) EBIT Margin	(7) FA Ratio	(8) FA Ratio	(9) FA Ratio	(10) Asset Turnover Ratio	(11) Asset Turnover Ratio	(12) Asset Turnover Ratio
Comptype	-0.35	-0.42	-0.41	0.30	0.13	0.16	-0.01	-0.01	-0.01	0.18	0.21	0.23
	(0.33)	(0.33)	(0.33)	(0.35)	(0.34)	(0.36)	(0.02)	(0.02)	(0.02)	(0.16)	(0.16)	(0.16)
$Dyear_1$	-0.11			-0.07			-0.01			-0.02		
	(0.20)			(0.21)			(0.01)			(0.07)		
DD_1	0.15			-0.06			0.00			-0.08		
	(0.23)			(0.30)			(0.01)			(0.12)		
$Dyear_2$		-0.05			0.32			-0.02^{*}			-0.02	
		(0.22)			(0.23)			(0.01)			(0.09)	
DD_2		-0.03			-0.41			0.02			-0.12	
		(0.25)			(0.29)			(0.02)			(0.13)	
$Dyear_3$			-0.14			-0.01			-0.02^{*}			0.00
			(0.21)			(0.23)			(0.01)			(0.10)
DD_3			0.03			-0.13			0.01			-0.07
			(0.26)			(0.31)			(0.02)			(0.17)
Constant	11.00^{***}	11.22^{***}	10.91^{***}	-3.27^{**}	-1.78	-2.12	0.03	0.05	0.04^{*}	-0.08	-0.08	-0.11
	(1.12)	(0.99)	(0.92)	(1.65)	(1.32)	(1.39)	(0.02)	(0.03)	(0.02)	(0.10)	(0.10)	(0.11)
Industry FE	X	X	X	X	X	X	X	X	X	X	X	X
N	321	323	321	322	323	321	324	330	333	324	330	333
R2	0.42	0.42	0.46	0.23	0.15	0.19	0.66	0.66	0.66	0.53	0.52	0.54

Table B10. Impact of Buyout Activity on Competitors' Financial Performance with Industry Fixed Effects

The table consists of coefficient estimates of OLS panel data regressions of respectively ROE, ROA and FCF to Assets on PE ownership. The specifications implement difference-in-differences estimation. ROE is defined as net income to equity, ROA as net income to total assets and FCF to Assets as the sum of EBIT and depreciation and amortisation, less net working capital, and capital expenditures to total assets. The sample initially consist of 96 pairs of close- and distant competitors, but may vary depending on the numbers of existing values of the performance measure being used. See Table B9 for explanations of all variables. Standard errors are clustered by individual company and in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1) ROE	(2) ROE	(3) ROE	(4) ROA	(5) ROA	(6) ROA	(7) FCF to Assets	(8) FCF to Assets	(9) FCF to Assets
Comptype	-0.59	-0.55	-0.47	-0.48	-0.48	-0.48	0.10	0.11	0.10
	(0.46)	(0.46)	(0.48)	(0.42)	(0.42)	(0.42)	(0.16)	(0.15)	(0.16)
$Dyear_1$	-0.92			-0.01			-0.01		
	(0.75)			(0.02)			(0.04)		
DD_1	0.87			0.33			-0.12		
	(0.76)			(0.36)			(0.14)		
$Dyear_1$		-0.87			0.01			0.01	
		(0.80)			(0.03)			(0.05)	
DD_2		0.65			0.31			-0.07	
		(0.81)			(0.29)			(0.13)	
$Dyear_3$			-0.97			-0.00			0.02
			(0.76)			(0.02)			(0.04)
DD_3			1.43			0.21			-0.16
			(0.93)			(0.30)			(0.13)
Constant	0.65	0.77*	0.49	0.18	0.19	0.23	-0.00	-0.07	-0.03
	(0.43)	(0.46)	(0.43)	(0.17)	(0.18)	(0.21)	(0.06)	(0.07)	(0.08)
Industry FE	X	X	X	X	X	X	X	X	X
N	324	330	333	324	330	333	316	322	325
R2	0.49	0.46	0.44	0.08	0.09	0.09	0.11	0.10	0.12

Table B11. Impact of Buyout Activity on Competitors' Distress Risk with Industry Fixed Effects

The table consists of coefficient estimates of OLS panel data regressions of respectively Leverage Ratio and Interest Coverage Ratio. The specifications implement difference-in-differences estimation. Leverage Ratio is defined as total debt to total assets, while Interest Coverage Ratio as EBIT to interest expenses. The sample initially consist of 96 pairs of close- and distant competitors, but may vary depending on the numbers of existing values of the performance measure being used. See Table B9 for descriptions of all variables. Standard errors are clustered by individual company and in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1) Leverage Ratio	(2) Leverage Ratio	(3) Leverage Ratio	(4) Interest Coverage Ratio	(5) Interest Coverage Ratio	(6) Interest Coverage Ratio
Comptype	2.12	2.08	2.23	366.48	525.89*	232.52
	(1.86)	(1.85)	(1.94)	(283.65)	(277.50)	(386.32)
$Dyear_1$	-0.06			-138.75		
	(0.04)			(116.40)		
DD_1	-1.11			178.68		
	(1.64)			(458.41)		
$Dyear_2$		-0.11			160.04	
		(0.11)			(126.63)	
DD_2		-1.11			-151.31	
		(1.26)			(472.50)	
$Dyear_3$			-0.16			31.70
			(0.11)			(138.11)
DD3			1.08			84.37
			(2.91)			(652.94)
Constant	-0.37	-0.27	-0.87	-224.78	-306.24	-271.46**
	(0.76)	(0.81)	(1.25)	(168.37)	(243.49)	(137.25)
Industry FE	X	X	X	X	X	X
N	324	330	333	225	229	230
R2	0.08	0.09	0.07	0.25	0.18	0.43