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The Effect of Venture Capital on Employment and Productivity

An empirical study of first round investments in Norwegian portfolio companies

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Master thesis, Major in Finance

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

The purpose of this thesis is to find out how private venture capital funding affects employment and productivity in Norwegian portfolio companies. To test this, we analyze employment and productivity in the period from 1995 to 2013 in 134 Norwegian companies that received venture capital funding in this timespan. We use propensity score matching to match the portfolio firms with similar, non-venture capital backed firms. We then perform difference-in-differences analyses to identify how venture capital funding affects employment and productivity in portfolio firms.

We find that companies backed by venture capital experience an increase in number of employees after the time of investment, where most of the increase occurs already in the investment year. The effect is persistent and significantly higher than for the matched control firms. Further, we find no evidence suggesting that portfolio companies grow at the expense of other competitors within their industry.

Our findings also suggest that firms backed by venture capital experience a drop in productivity after the investment. The drop is immediate, and brings the portfolio firms down to lower productivity levels than their matched control firms. We find nothing indicating that the differences in productivity levels even out over time.

Preface

This thesis is written as a part of the Master in Finance at the Norwegian School of Economics (NHH) and represents the end of five years of higher education.

We initiated the work by discussing topics that we both wanted to engage in. Venture capital is an area of research that we find interesting, and we decided that we wanted to explore this topic further. The process has been challenging yet exciting, and we have gained valuable knowledge about the venture capital industry.

Several people have helped us during the research period. First, we would like to thank our supervisor, Associate Professor Tyler Hull, for guidance and help along the way. We also want to thank Associate Professor Carsten Bienz for providing us with data on Norwegian private equity deals. In addition, we appreciate the help from Associate Professor Aksel Mjøs, who gave us access to SNF's and NHH's database of accounting and company information.

Bergen, December 2015

Anna Sandli Danbolt Marte Øverby Tennøe

Content

1. Introduction

This chapter provides an introduction to the thesis. We start by presenting the motivation and background for our chosen area of research. We will then formalize our research questions, before we give a brief summary of our main results. Lastly, we provide an overview of the structure of the thesis.

1.1 Background and Motivation

Due to declining oil prices, Norway has experienced an increase in the unemployment rate during the past year. 80,000 people were registered as fully unemployed by the end of October 2015, which represents an increase of 7,900 people from October 2014 (Armstrong, 2015). The Norwegian Labour and Welfare Administration (NAV) expects additional 10,000 unemployed people next year, while an unpublished report by Menon and Business Economics and DNV GL depicts a worst-case scenario of 200,000 lost jobs from 2014 to 2020 (Taraldsen, 2015). It is therefore evident that Norway will be more dependent on growth in other sectors than the oil sector to support growth in the economy in the future.

Entrepreneurship and innovation have been highlighted as important focus areas in terms of job creation. The Norwegian Government newly launched a nationwide entrepreneurship plan, which emphasizes the importance of facilitating entrepreneurship in order to create new jobs. The plan presents different initiatives worth over NOK 400 million, where easier access to venture capital (VC henceforth) is one of them (Ministry of Trade, Industry and Fisheries, 2015).

We think the relationship between VC and job creation is interesting, and we therefore want to study the effects of VC funding on employment in Norwegian portfolio firms. Do VC investments accelerate employment growth in start-up companies? Is the growth relatively higher than growth in similar non-VC backed firms? In addition, we also think it would be interesting to dig deeper into the net effect on employment. If VC backed firms grow, they might grow at the expense of other firms within the same industry. If this is the case, the net effect on job creation in the Norwegian economy will be ambiguous.

In countries with relatively high levels of employment, productivity growth is one of the most important sources of value creation (Ministry of Trade, Industry and Fisheries, 2013). In

Norway, the productivity growth has gone down in recent years, and the Norwegian Government has expressed that it will focus more on increasing the productivity growth (Jensen and Solberg, 2015). Motivated by this, we also want to study how venture capitalists (VCs henceforth) affect the productivity in VC backed firms.

1.2 Research Questions

Based on the presented background and motivation, we will try to answer the following three research questions:

I) How do VC investments affect employment in portfolio firms?

II) Does the presence of VC backed firms affect employment in competing firms?

III) How do VC investments affect productivity in portfolio firms?

1.3 Main Results

First, we find that VC funding leads to an increase in number of employees in portfolio companies, relative to similar non-VC backed companies. Overall, VC funding contributes to an increase of 64 percent in the employment level in portfolio firms, and a large part of this arises already in the year of investment. The positive differences hold both in a short- and in a long-term perspective, indicating no reversal effect. When analyzing annual growth effects, we find that VC entry increases employment growth by 12 percentage points in the year of investment. In the subsequent years, we find no significant differences in growth rates between the two groups.

Second, we examine whether VC backed firms grow at the expense of other companies within their industry. We analyze the impact of active VC backed firms on annual employment growth in other firms, using different measures for VC activity. In sum, we find no reason to claim that the presence of VC backed firms has negative effects on employment growth in other, non-VC backed firms.

Third, we find that portfolio firms experience a significant drop in productivity after VC entry, relative to similar non-VC backed firms. Overall, VC funding contributes to a decrease in productivity levels of 37 percent. The negative differences between the two groups are evident both in a short- and long-term perspective, and the drop appears already in the year of investment. When analyzing growth effects, we find that the productivity growth drops by 27 percentage points in the year of VC entry. However, we find no clear differences in growth rates beyond this point.

1.4 Structure of the Thesis

In chapter 2, we provide a summary of previous research related to our chosen topic. Chapter 3 contains a description of private equity and venture capital, and chapter 4 presents theory of why VC backed companies may perform better than other companies. In chapter 5, we provide a presentation of our dataset. Here, we describe our sources of data, as well as how we identify VC backed companies and their matched control firms. In addition, we present biases that we believe are relevant for our research. Chapter 6 presents the methodology we use to answer our research questions. In chapter 7, we present and interpret our results. Chapter 8 contains a summary of our results, limitations of our thesis and suggestions for further research.

The output from our tests and some descriptive statistics can be found at the end of the thesis.

2. Related Research

In this chapter, we present previous findings related to our chosen area of research. The majority of former studies on private equity focus on the buyout segment. In a working paper from the National Bureau of Economic Research, Davis et al. (2011) analyze job creation and destruction in American companies with late stage ownership changes. By using propensity score matching, they are able to identify similar companies in terms of age, size, former growth and number of establishments. When comparing target companies with matched controls, they find evidence of a drop in employment after acquisition. The drop is, however, largely dependent on which industry the target firms operate in.

In a discussion paper issued by the Centre of European Economic Research, Engel (2002) analyzes the effect of VCs' and other investors' involvement in young, innovative and fast growing firms in Germany. He finds that surviving VC backed firms achieve significantly higher employment growth rates, because of the financial involvement and the services provided by the VCs. Further, Engel finds that VCs are better suited to push the portfolio companies to a faster and higher growth during the time of the venture, relative to other investors.

Belke, Fehn and Foster (2003) analyze VC backed companies in 20 OECD countries, and provide empirical evidence of a causal relationship between VC funding and employment growth at the macro level. The authors argue that job creation might also depend on markets that are complementary to the labor market, and thus, they include capital market variables in their analyses. They find that VC funding significantly raises employment growth and job creation. However, they state that VC funding mainly contributes to job creation in new and innovative companies.

Alemany and Martí (2005) analyze a sample of over 300 Spanish VC backed firms from 1989 to 1998 to study the economic impact of VC funding, where growth in employment is one of their variables of interest. They look at the effect over time, and compare the results to a control group of similar non-VC backed firms. They analyze average annual growth from the year of investment and three years ahead, and find evidence to support that several variables, including employment, grow faster in VC backed firms.

Croce, Martí and Murtinu (2013) study the performance of European VC backed firms[1] in high-tech industries, and compare them to a matched control group. They analyze the productivity growth before and after the first round of VC investment, using different measures for productivity. They find that total factor productivity and capital productivity growth are significantly higher in VC backed firms during the holding period. However, they find no significant differences in labor productivity growth between the two groups.

Relatively few research papers focus on how VC investments affect employment and productivity in Norwegian portfolio firms. In a publication from Menon Business Economics, Grünfeld and Grimsby (2008) study the economic impact of VC and private equity investments in Norway. They analyze how employment develops in private equity and VC backed firms, and look at how the investments contribute to society in terms of tax payments and regional job creation. They find that this type of ownership strongly promotes employment growth, and find no reason to claim that the economy suffers due to the presence of VC and private equity ownership. Rather, the portfolio companies contribute with higher tax payments and wage bills.

[1] The countries included in the research are Belgium, Finland, France, Italy, Spain and the United Kingdom.

3. Introduction to Private Equity and Venture Capital

The British Private Equity & Venture Capital Association (BVCA, 2015) defines private equity (PE) as “finance provided in return for an equity stake in potentially high growth companies”. PE firms are median to long-term investors, and the investment horizon is typically five to seven years (BVCA, 2015). The ultimate goal for the investor is to realize returns by exiting the business in better shape than when it was acquired (BVCA, 2015). The most common exit routes are trade sale to an industrial buyer, secondary sale to another PE fund, listing through initial public offering and sale to the management group (CapMan, 2012). To obtain best possible returns, PE firms often specialize in certain industries and/or stages of the portfolio companies’ life cycle.

3.1 Different Types of Private Equity

One can divide PE into different segments, where the main distinction is between VC and buyout investments. These segments relate to the life cycle stage of the portfolio company.

According to Argentum (2015), VC is a subset of PE and refers to equity investments made to fund an early stage, i.e. seed and start-up, or expansion venture. In this context, investments in seed companies involve financing provided to research, assess and develop an initial concept. Further, the start-up stage refers to financing provided to companies for development of products and initial marketing. Investments in companies within the expansion stage involve providing capital for the growth and expansion of a company. In this thesis, we will refer to investments in seed, start-up and expansion stages as VC investments.

The buyout segment typically relates to investments in larger and more mature portfolio companies. Argentum defines a buyout transaction as an acquisition of a business, business unit or company from the current shareholders (Argentum, 2015). As this thesis focuses on VC investments, we will not describe the buyout segment in more detail.

4. Theory

In this chapter, we present theory that can explain why VC backed companies may perform better than their competitors.

4.1 The Role of Ownership

The following theory is based on the book *Hvem eier Norge?* [Who owns Norway?], written by Grünfeld and Jakobsen (2006).

Grünfeld and Jakobsen have developed a framework for how owners can add value to their company. They highlight the following four roles of the owner:

1. Selection
2. Fuel
3. Complementary resources
4. Guidance

By filling these four roles, the owners will contribute with competent capital to the company. We will now describe the roles in more detail, with focus on what is relevant for VC ownership.

4.1.1 Selection

The role of selection is about identifying the investment objects that will yield the highest possible returns for the owners. Selecting companies and investment objects requires financial expertise, as well as the ability to evaluate technology, the organization, consumer behavior and competitiveness. One also need to keep in mind that the ability to add value differs among investors, and that the investors often have different risk preferences and time perspectives. Thus, the selection process is not a zero-sum game, but rather a value-adding role.

4.1.2 Fuel

Grünfeld and Jakobsen refer to capital as fuel. Capital injections can work as an accelerator, and draining capital can be seen as a brake for the company. The injections are relevant for all stages that require investments. However, Grünfeld and Jakobsen state that the demand for capital is highest in early stages.

In private equity, the initial capital injection is usually followed by several larger follow up investments. This is because the demand for capital often arises at different points in time, and it is easier to maintain control if the owner conducts sequential injections in the portfolio company.

VCs contribute with “fuel” to innovative companies. Besides funding already existing ideas, the chances of receiving funding also work as an incentive for potential future entrepreneurs. Hence, these investors also contribute to promote future innovation.

4.1.3 Complementary Resources

For a company to operate efficiently in a market, it is dependent on several factors. For example, it is important to create a relationship with suppliers and customers, as well as to attract people with relevant expertise. While the entrepreneurs often have good knowledge of the product, they usually do not possess other skills required to succeed commercially. PE funds, however, specialize in providing the right resources in certain stages in a company’s life cycle. Hence, they can build a pool of resources tailor-made for the relevant stage. Through active ownership, the portfolio company can access complementary resources that are essential for future value creation.

4.1.4 Guidance

According to Grünfeld and Jakobsen, guidance can be described as a continuous four-step process, as illustrated by Figure 4-1. The first step is about defining the mission and goals of the company. The second step involves creating a strategy to make sure that the defined goals will be reached. After designing the strategy, the third step is to implement it the right way. Even though step two and three both are tasks mainly performed by the management, the owners should nevertheless engage in these activities to make sure the company reaches the defined goals. The latter represents the fourth step in the process, which is known as control and monitoring.

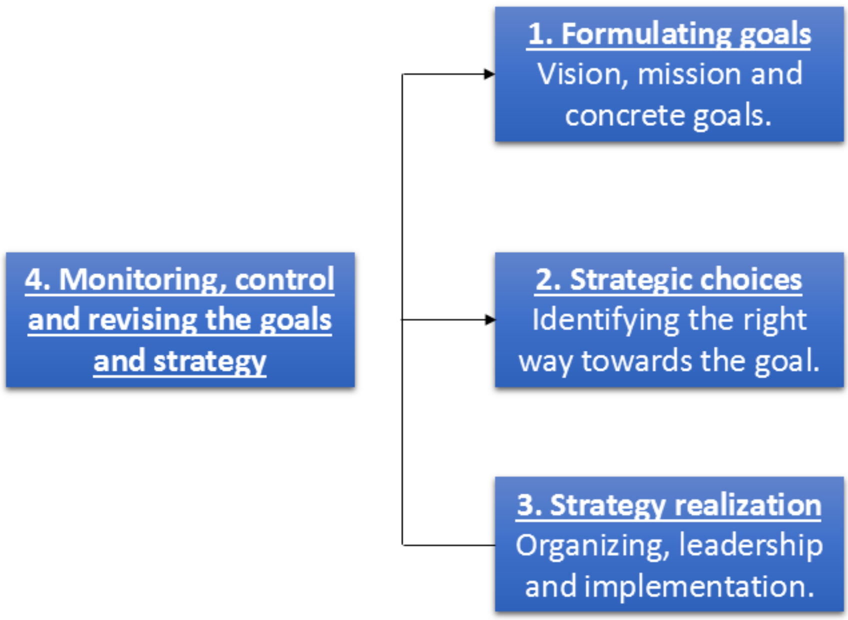


Figure 4-1: The four steps of guidance

5. Dataset and Possible Biases

We will now present the data used in our analysis. We start by introducing the sources of our data. Further, we describe the process of identifying VC backed companies and their comparable companies. In the last section, we look at possible biases that may affect the results.

5.1 Sources of Data

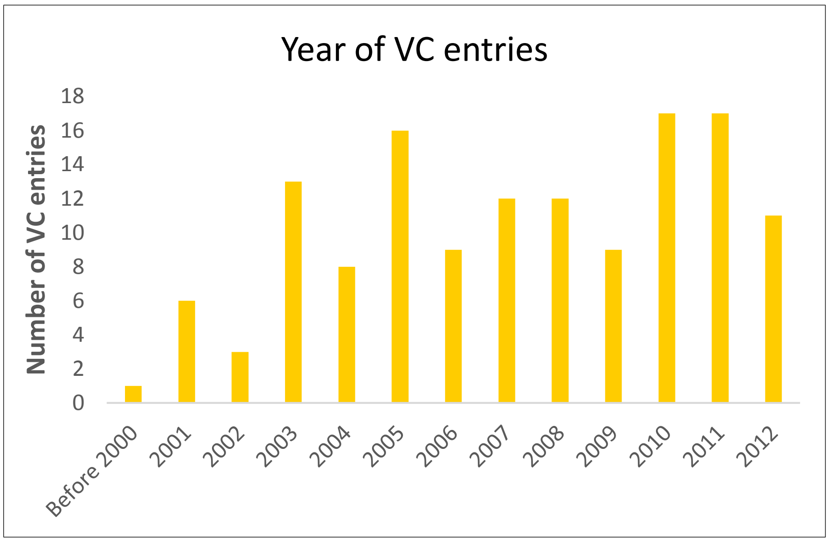
Our main source of data is the accounting database from the Centre for Applied Research at NHH (SNF). This database contains accounting data and company information for all Norwegian companies from 1992 to 2013. It underwent comprehensive revision in 2013, where one of the latest updates was a supplementation of number of employees from NAV back to 1995 (Berner, Mjøs and Olving, 2014).

To retrieve information about VC transactions, we were granted access to the database of Argentum Centre for Private Equity (ACPE) at NHH. By using this database, we gained information about Norwegian portfolio companies, including name of fund and fund manager, date of entry and investment stage.

5.2 Identification of VC Backed Companies

As described above, we use information from the ACPE database to identify VC backed companies. The scope of our thesis is limited to Norwegian portfolio companies that have received investments from Norwegian VC funds. We exclude portfolio companies backed by foreign funds, due to relatively few observations and some missing values. In addition, foreign ownership may affect portfolio companies in a slightly different way, which is not something we look into. Further, we exclude portfolio companies registered as buyout transactions, as we only focus on early stages in this thesis. In the database, the main classifications are seed, venture and buyout, and our sample includes portfolio companies registered as seed and venture. As described in section 3.1, we use the collective terms VC investments and VC backed firms.

To obtain a large sample of VC backed companies, we study portfolio companies that have received first round of VC investment between 1995 and 2012. As Graph 5-1 illustrates, the majority of VC entries in our sample occur after 2003. However, we believe that including more years (and thus more observations) will improve our analysis. A long time span covers both booms and recessions in the economy, and any significant results may therefore be generalized to apply for other time periods and different economic conditions.



Graph 5-1: The distribution of VC entries in our timespan

Even though we have information about VC investments from Argentum's database prior to 1995, we are dependent on having information about employment from the SNF database. Employment information is limited before 1995, which is why we exclude any VC investments prior to this year. We also remove portfolio companies with first round of VC investment after 2012, as we do not have accounting data after 2013.

Further, we exclude portfolio companies with missing fund entry dates. This is because we want to analyze a potential VC effect in the years following the first round of investment. If one or more fund entry dates are missing, it is difficult to identify which investment is the first, and we therefore choose to remove these companies from our sample.

5.3 Identification of Comparable Companies

In order to analyze the VC effect on employment and productivity in Norwegian portfolio companies, we need to compare the VC backed companies (target group) to similar and comparable non-VC backed companies (control group). We use propensity score matching to find comparable firms, based on some observable characteristics pre-VC entry. More specifically, we match each target firm with a control firm, based on characteristics one year before the target received first round of VC investment. We choose one year before as a reference year, because we want the two groups to be as similar as possible *ex ante,* and we want to make sure that any potential VC effects had not yet affected the portfolio companies. We describe propensity score matching in more detail in section 6.1.

To find control companies for our VC backed companies, we have to decide which characteristics our matching should be based on. According to previous research on similar topics (see for example Davis et al., 2011), industry, firm size and firm age are characteristics that have impact on a firm's growth, and should therefore be included in the matching. We also add geographical region as a matching criterion, as there might be differences between the different regions in Norway. In summary, our matching is based on the following:

- Same calendar year (the year before VC entry)
- Same industry, based on the five-digit NACE code
- Similar size, measured in number of employees
- Similar age, based on year of incorporation
- Similar region

The first two are set as strict requirements, forcing exact matching on industry and calendar year. The remaining three characteristics may deviate if no exact match is found. However, due to our large pool of potential control companies, most matched controls are very similar to their respective target at the time of matching. To the best of our knowledge, none of the companies in the control group have received any type of PE investment.

We also considered adding previous growth in employment (i.e. before VC entry) as a matching criterion. However, as many of our target firms only have been active for one year before VC entry, we were not able to create such a measure for all firms. Another issue is that percentage growth can vary a lot for small and midsize companies. For example, an increase from two to four employees represents a 100 percent increase. Matching on previous growth could easily lead to an exclusion of a potential control firm that increases its number of employees from three to four, even though the two firms could be a good match. Hence, we choose not to use previous growth as a matching criterion.

5.4 Constructed Variables

We will now give a brief description of the variables we have constructed in our dataset. The term "treatment" refers to VC funding, while "target firms" and "targets" refer to firms that have received or will receive VC funding.

Employment

Variable equal to the logarithm of number of employees+1 on firm level. We use the logarithm to adjust for skewness towards large values. We use employees+1 in order to avoid mathematical error in the cases where the number of employees is equal to zero.

Employment growth

Variable equal to annual changes in the logarithm of employees+1 on firm level, calculated as log($employees_t$ +1)– log($employees_{t-1}$+1).

Industry employment growth

Variable equal to annual changes in the logarithm of employees+1 on industry level, calculated as log($employees_t$+1)-log($employees_{t-1}$+1) for each five-digit industry code.

Productivity

Variable equal to the logarithm of sales revenues divided by payroll expenses on firm level. We use the logarithm to adjust for skewness towards large values. Sales revenue is in the numerator, as this represents the core activity of the company. We prefer sales rather than reported net income, as net income in startups often is sensitive to depreciation expenses. We prefer payroll expenses rather than number of employees in the denominator, because we want the productivity measure to reflect sales revenues per amount invested in the labor force.

Productivity growth

Variable equal to annual changes in the logarithm of sales revenues divided by payroll expenses on firm level, calculated as log(sales $revenues_t$/payroll $expenses_t$) - log(sales $revenues_{t-1}$ /payroll $expenses_{t-1}$).

Treatment

Dummy variable equal to one for all VC backed firms and zero for all control firms. This variable does not take into account *when* the target firms receive VC funding, but is equal to one in all years for these firms.

After

Dummy variable equal to one in the year of VC entry and onwards for each VC backed firm and their matched control. As a result, we can distinguish between “before” and “after” VC entry for both targets and their matched controls.

*Treatment*After*

Interaction variable equal to one in the year of VC entry and onwards for VC backed firms.

VC entry time dummies (t+X)

Dummy variables equal to one in different years following VC entry. For example, *t+1* is equal to one if the observation is one year after VC entry. This applies both for targets and for their matched controls.

*Treatment*VC entry time dummies*

Interaction variables equal to 1 in different years following VC entry for VC backed firms.

VC activity

Variable that measures the degree of VC activity, measured as number of active VC backed companies in a given industry for a given year.

VC activity dummy

Dummy variable equal to one if there are one or more VC backed companies present in the industry the given year, zero otherwise.

5.5 Possible Biases

We will now present the biases we believe are most relevant for our research. In the first two subsections, we present biases related to our sample of data, namely selection bias and survivorship bias. Lastly, we will present a potential bias related to our matching procedure, and discuss whether incomplete matching can influence the results.

5.5.1 Selection Bias

Selection bias is an error introduced when the study population does not represent the population intended to be analyzed (Delgado-Rodríguez and Llorca, 2004). In our case, the selection of portfolio companies can lead to such a bias. For an investment to take place, the VCs will screen potential candidates, and aim to invest in the firm with the greatest probability of high returns. This means that our target firms may already have large potential for growth, since the VCs have chosen them. If this is the case, one should expect that VC backed firms grow more than comparable firms due to the nature of these firms, and not due to the VC entry.

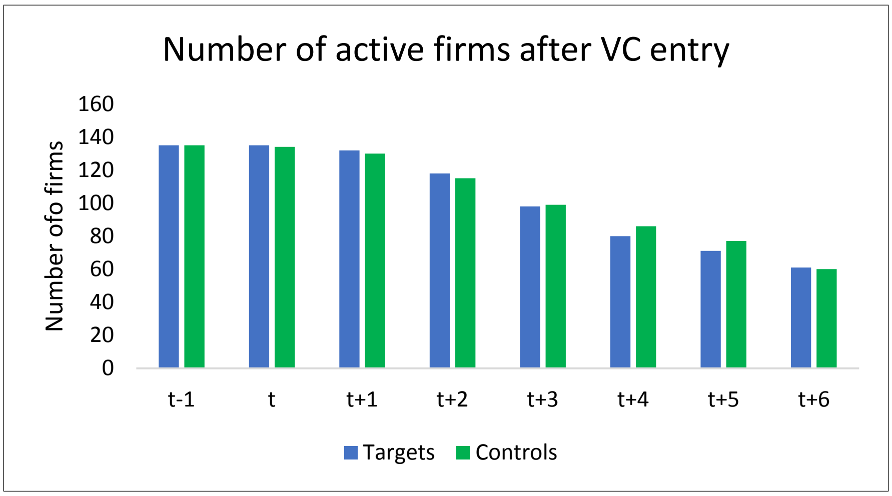
At the same time, the owners of the firms must be willing to accept the terms from the VCs. It can be plausible to assume that any firm with high growth ambitions would want a VC investor as an owner, because the investor will contribute with experience and other resources that the firm needs in order to reach its goals. Then again, one can also assume that some of the best firms do not consider VC funding, because they do not want to lose control and ownership. If they have great probability for success, it should be possible to get access to capital elsewhere. If this is the case, one should not expect VC backed firms to grow faster than other firms. In fact, some of our control firms may have considered VC funding or VCs may have considered investing in some of our control firms. However, we do not have any information about this.

VC funding is a result of mutual acceptance, which is something one has to keep in mind when reading this thesis. Optimally, we would want to eliminate any biases related to the selection process, in order to isolate the effect of VC ownership. For example, we could use potential for growth as one of the matching criteria as an attempt to improve the matching procedure. However, potential is very difficult to measure, as it depends on several different factors. We therefore settle with the matching procedure described in section 5.3.

5.5.2 Survivorship Bias

Survivorship bias is another bias that can influence our results. It arises when failed companies are excluded from the analysis. As a result, only the successful companies remain in the analysis, and this causes the results to skew higher than it should (Moen and Riis, 2001). In our dataset, both target and control firms disappear for different reasons. The main reason is that many companies received VC funding only a few years ago. For example, several targets received VC funding between 2010 and 2012, which, given our timespan, shortens the reported post-VC period down to only a few years. Further, we also know that bankruptcy causes some firms to drop out. Other explanations can be mergers and acquisitions, or dissolution of the firm.

Due to the reasons mentioned above, the number of active firms decreases with the number of years after VC entry. However, this applies for both target and control firms. By looking at Graph 5-2, we see that there are no major differences between targets and controls regarding how many companies that fall out in the years after VC entry. Given that the main reason for a declining number of observations is recently VC backed firms, we will argue that survivorship bias is not a major concern for our further analysis.



Graph 5-2: Number of active targets and control firms the years after VC entry

5.5.3 Bias Due to Incomplete Matching

Rosenbaum and Rubin (1985) show that the bias due to incomplete matching can be severe. They introduce the median absolute standardized bias as a measure of differences between treatment and control group before matching. The standardized difference between the means for a given covariate (x_i) can be written as[2]:

$$B(X_i) = 100 * \frac{\bar{X}_{i1} - \bar{X}_{i0}}{\sqrt{\frac{1}{2}(V_1(x_i) + V_0(x_i))}}$$

[2] The formula is formalized by Becker and Hvide (2015), based on the work of Rosenbaum and Rubin (1985).

$\bar{X}_{i1}$ is the unit mean for the treated observations, and $\bar{X}_{i0}$ is the corresponding unit mean for controls. $V_1(x_i)$ and $V_0(x_i)$ denote the sample variances in the treated and the control group, respectively.

According to Rosenbaum and Rubin (1985), a value of 20 is "large", meaning that there are substantial differences between the target group and control group *ex ante*. For our matched sample, the median absolute standardized bias is 8.2. Even though this number is significantly lower than 20, it indicates that the matching has not managed to remove all the differences in pre-treatment characteristics between targets and controls. This should be kept in mind while interpreting the results in the analysis.

6. Methodology

In this chapter, we will present the methodology used in our analysis. We start by describing the propensity score matching in more detail. Further, we describe the regressions we conduct in the analysis. This includes a description of the difference-in-differences estimator and the corresponding regression model setup.

6.1 Propensity Score Matching

Propensity score matching is a matching technique used on observational data. In many studies, there are often small groups of subjects exposed to treatment, relative to the untreated control subjects. Matched sampling attempts to choose the controls that are most similar to the treated subjects with respect to measured background variables (Rosenbaum and Rubin, 1985). These specified background variables are known as covariates, and are assumed to affect the probability of being treated. By controlling for these covariates, the propensity score matching attempts to reduce potential biases due to confounding variables. Rosenbaum and Rubin (1983) show that matching based on propensity scores, when successful, tend to balance the observed covariates.

The estimated probability of being treated, i.e. the propensity score, can be expressed as

$$P(X) = Probability\ (d = 1) |\ X$$

where d = 1 indicates a treated observation, and X denotes the observable characteristics used in the matching (Herzog, 2008). In accordance with the methodology, propensity scores are derived for all entities. Based on the size of the propensity scores, targets are matched with controls. This means that the target's match is the control firm with the most similar propensity score.

6.2 Regression Analyses

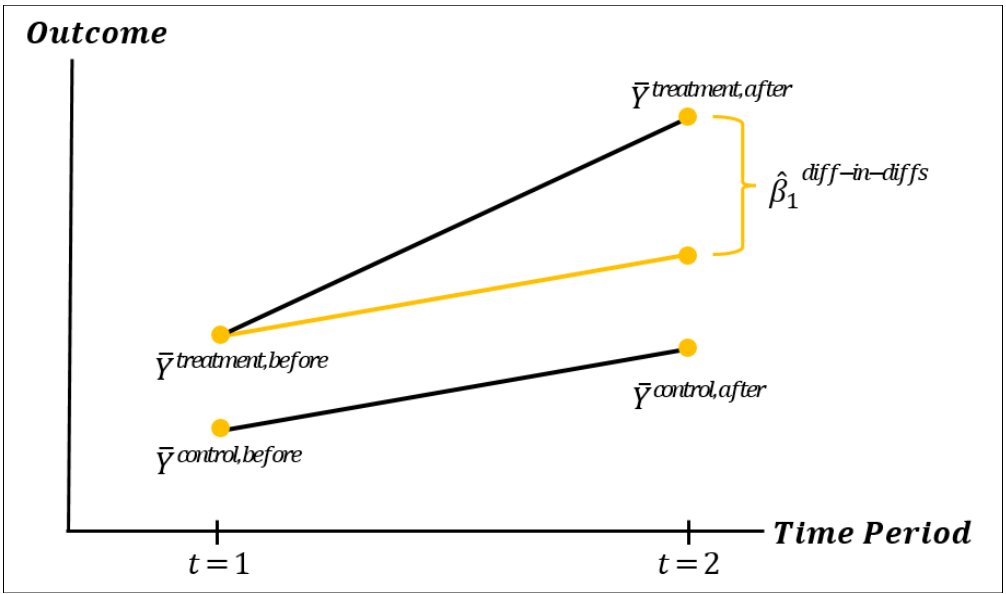
In general, regression analysis is a way of estimating the relationship between variables. When performing regressions on longitudinal data, we are also interested in capturing changes over time. The majority of the regressions in this thesis are difference-in-differences analyses. We will now describe this type of regression model in more detail.

6.2.1 Difference-in-Differences Regression

The difference-in-differences regression is a tool used to estimate the effect of a treatment, see for example Card and Krueger (1994). By comparing the differences in outcome pre- and post-treatment for a treated and a control group, one can derive the difference-in-differences estimator (Waldinger, 2014). The estimator is defined as:

$$\beta_1{}^{diff-in-diffs} = \left(\bar{Y}^{treat,after} - \bar{Y}^{treat,before}\right) - \left(\bar{Y}^{control,after} - \bar{Y}^{control,before}\right)$$

$\bar{Y}$ denotes the outcome variable for treated and controls, and β_1 is the difference-in-differences estimator. Graph 6-1 illustrates this relationship.



Graph 6-1: The difference-in-differences estimator

Model Setup

Instead of performing regression analyses using the whole sample of data, we only include the target firms and their matched controls. The main reason for doing so is that the 'after'-period for non-VC backed firms cannot be defined unless they are picked as a match for a target firm. Because we restrict the matching within the same calendar year, we can define 'before' and 'after' VC entry both for target firms and control firms. Another reason is that targets and potential controls are not necessarily similar before VC entry. The matching will therefore allow us to compare target firms with their best matches – based on observable pre-treatment characteristics – instead of also including non-VC backed companies that are not similar at all.

For these reasons, we use the matched sample in the difference-in-differences analyses, including 134 targets and 134 controls.

We run difference-in-differences panel regressions to analyze differences between target firms and matched control firms before and after VC entry. The regressions are of the following type[3]:

$$Performance\ indicator_{it} = \alpha + \beta_1 * Treatment_i + \beta_2 * Treatment_i * After_{it} + \beta_3 * After_{it} + \gamma * X_{it} + \delta_t + \varepsilon$$

As defined in section 5.4, *Treatment* is a dummy variable and is equal to one for all targets. *After* is also a dummy variable and it changes from zero to one in the year of VC entry, both for targets and their matched control firms. This means that if a target receives its first VC investment in 2005, *After* will be equal to zero from the year of incorporation to 2004, and equal to one from 2005 and onwards. The same applies for its matched control firm. *X* represents firm characteristics (industry, region and firm size), and δ represents year dummies.

Our focus is on the coefficient of the constructed interaction variable (β_2), as it captures the difference-in-differences between targets and control firms after VC entry. If it is significantly different from zero, VC funding has an effect on the dependent variable. In addition, β_1 will also be of interest, because it indicates whether there are fundamental differences in the outcome variable between the target and control group. Optimally, this coefficient should not be significantly different from zero, as we want the target and control group to be as similar as possible *ex ante*.

Further, we will expand the regression analysis by dividing the 'after'-period into several post-treatment periods. By generating specified interaction variables for each year after VC entry, we are able to separate any short-term and/or long-term effects of VC entry on the outcome variable. We are interested in the coefficients for these different interaction variables, as they will measure the difference-in-differences between target firms and control firms one year, two years, three years etc. after VC entry.

[3]In the analysis, *Performance indicator* represents either level of employment, employment growth, level of productivity or productivity growth. We use a similar model specification as Becker and Hvide (2015).

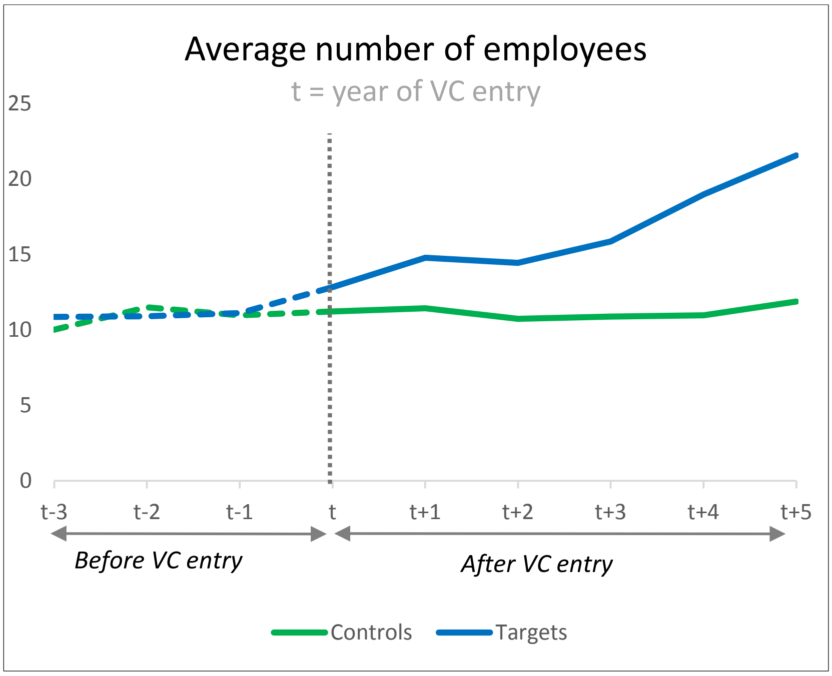
7. Analysis

We start by providing the reader with an introduction to the analysis, where we scratch the surface of the data. Then we present the results from the analyses, in order to answer our three research questions. To answer the first question, we test whether there are significant differences in employment between targets and matched controls before and after VC entry. In order to answer the second research question, we test whether the degree of VC activity affects employment in other, non-VC backed companies. We will then answer the third research question by testing whether VC entry affects the productivity in portfolio firms.

7.1 Introduction

In this section, we will describe and illustrate the main features of our data. Throughout the analysis, we define the year of treatment as "t", and thus t+X represents X years after treatment. "t-1" refers to the year before treatment, i.e. the year of matching.

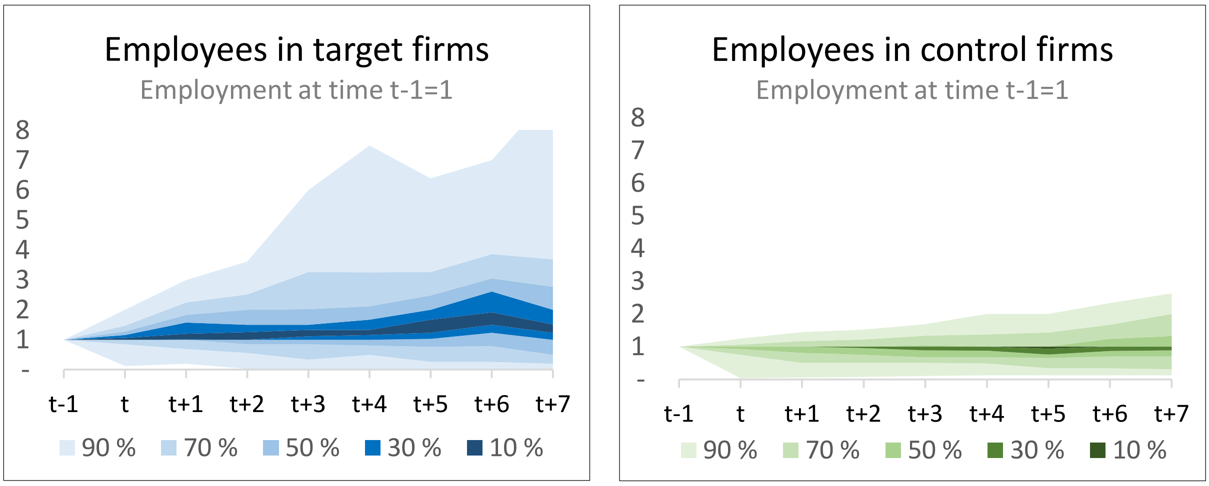
We start by plotting the average number of employees in target and control firms the years before and after VC entry, illustrated in Graph 7-1. The aim is to check whether we can identify any clear differences just by looking at the development in employment. The Y-axis displays average number of employees, and the X-axis displays the timespan.



Graph 7-1: Average number of employees for targets and controls before and after VC entry

As the graph illustrates, the average number of employees is similar for the two groups up until the year before VC entry. After that point, the two groups seem to develop differently. Rather than continuing at the same level as controls, the targets experience a significant increase in employees after VC entry. With the exception of two years after VC entry, the employment in target firms continues to grow throughout the given timespan.

Second, we want to take a closer look at the spread in number of employees for targets and controls after VC entry, to get an impression of the differences within the two groups. Thus, we plot the observations in both groups from the 10th to 90th percentile. Graph 7-2 and Graph 7-3 show the spread for targets and controls, respectively. The Y-axis is an index, where the number of employees in the year before VC entry (t-1) is set to one. The X-axis denotes the timeline. As the graphs illustrate, the differences within the target group are large compared to the differences within the control group. Three years after VC entry, 90 percent of the targets are situated between zero and six on the index, where six indicates a six-fold increase in employees. In comparison, the corresponding interval for controls are between zero and two on the index. In the next section, we want to dig deeper into the differences identified in this section, and hopefully be able to quantify the VC effect on employment.



Graph 7-2 and 7-3: The spread in number of employees in target and control firms

For more information about our dataset, please see the descriptive statistics at the end of the thesis.

7.2 Research Question I: How Do VC Investments Affect Employment in Portfolio Firms?

From what we saw in section 7.1, targets seem to experience employment growth after VC entry relative to the matched control firms. In this part of the analysis, we will try to quantify the effect of VC investment on employment in target firms by performing difference-in-differences analyses. To make sure that we compare the targets with companies that are similar *ex ante*, we use our matched controls as basis for comparison. We control for firm fixed and year fixed effects, as well as firm size[4].

Our focus is on how VC investments affect the level of employment and annual employment growth. The analysis of level effects is of interest because it provides information about how VC investments can contribute to net job creation in target firms, and whether the effect sustains. When analyzing level effects, we run regressions of the following type:

$$Employment_{it} = \alpha + \beta_1 * Treatment_i + \beta_2 * Treatment_i * After_{it} + \beta_3 * After_{it} + \gamma * X_{it} + \delta_t + \varepsilon$$

By analyzing annual employment changes, we can identify how employment in target firms changes from one year to another relative to control firms. When analyzing annual growth effects, we run regressions of the following type:

$$Employment\ growth_{it} = \alpha + \beta_1 * Treatment_i + \beta_2 * Treatment_i * After_{it} + \beta_3 * After_{it} + \gamma * X_{it} + \delta_t + \varepsilon$$

7.2.1 Employment: Level Effects

We start by running a regression where we look at the overall differences in the level of employment before and after VC entry for targets and controls. Table 7-1 presents the regression results[5]. We see that *After*Treatment* is significant on a one percent level, and we can therefore reject the null hypothesis which states that VC entry does not have a significant impact on the level of employment in target firms. In other words, we can conclude that after receiving their first round of VC investment, targets experience a significant increase in

[4] Firm fixed effects include region and industry group. Firm size is measured as total assets per December 31 the year before.

[5] The interpretation of the results is based on the first column in the table, marked as (1).

number of employees. The size of the effect is large – the mean effect of VC entry on employment is 64 percent[6]. The table also presents other regression specifications, where we change the control variables as a robustness check. The results are, however, relatively similar.

We are also interested in the coefficient of the *Treatment*-dummy, as this provides for a test of (a lack of) pre-treatment effects. The result shows that it is not statistically significant, which suggests that there are no overall pre-treatment effects in the level of employment.

In sum, the results indicate that there is a positive overall effect of VC funding on the level of employment in target firms.

Next, we expand the regression and replace the *After*-dummy with several post-treatment period dummies as described in section 6.2.1. As a consequence, the interaction variable *Treatment*After* is replaced by interaction variables for each post-treatment period[7]. Table 7-2 presents the regression results.

First, we find that the VC effect on employment levels in the year of entry is 46 percent and significant at a one percent level. This indicates that VC entry has a large impact on the level of employment in VC backed firms already in the year of entry. One reason can be that the VCs quickly restructure the target firms to accelerate growth, by e.g. bringing in relevant expertise required to succeed. Further, there are also positive differences in the years following the VC entry. After three years, the VC effect is 66 percent, indicating that the differences between targets and controls continue to increase in the years following the investment.

Further, we can see from Table 7-2 that the positive effect on the employment level is present in a longer run as well. It is, however, important to keep in mind that this regression is based on the number of employees each year, rather than employment changes from one year to another. This means that an increase in the level of employment for a given year will be present in subsequent years as well, unless there is a reversal effect.

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[6] With log dependent variables, we use exp(coefficient)-1 to find the percentage effect of the variable: exp(0.4975)-1= 0.6446. This approach applies for all the analyses of level effects in this thesis.

[7] As we are most interested in the VC effect on employment in the first years following VC entry, we have one interaction variable for each year up until three years after VC entry. We also have one interaction variable representing all the following years, i.e. “the longer run”.

In sum, we have found that VC investments lead to net job creation in target firms, and we find no evidence indicating a reversal effect within our timespan.

7.2.2 Employment: Growth Effects

We will now perform the same types of regressions as in the previous section, but we use annual employment change rather than the level of employment as dependent variable. We start by conducting the basic before/after regression, in order to study the overall effect of VC funding on employment growth. Table 7-3 presents the regression results, and we see that the results are different from the corresponding level-analysis. The interaction variable *Treatment*After* is no longer significant, and we cannot conclude that VC investments have an overall effect on annual employment growth.

By now, we know that the level of employment increases after VC entry, but we have not managed to identify any overall effects of VC funding on employment change. However, this does not mean that there are no differences between the two groups in some of the years following VC entry. Therefore, we will examine the after-period in more detail. We expand the regression analysis in the same way as we expanded the analysis of level effects. Table 7-4 presents the regression results.

Our results suggest that VC funding increases employment growth by 12 percentage points in the year of investment[8]. The coefficient is significant at a 10 percent level. Somewhat surprisingly, we find no results indicating that VC investment leads to significant differences in annual employment growth beyond the year of VC entry. This indicates that the annual employment growth in target firms develops similarly as for the control firms after the investment year.

Note that the *Treatment*-dummy is statistically significant in both the simple and the expanded regression analysis. The results indicate that target firms in general grow by ten percentage points more than the control group, independently of VC entry. Optimally, we would want there to be no such pre-treatment differences between the two groups. However, as we chose not to include previous employment growth as a matching criterion, we knew this was a

[8] When the dependent variable is the first difference in logarithms, we use exp(coefficient)-1 to find the effect of the variable. Multiplied by 100, the effect can be interpreted as percentage points. This approach applies for all growth analyses in the thesis.

possible outcome. Note that the general differences should not affect the additional growth that arises due to VC entry, which means that our findings still provide interesting indications of how VC funding affects employment growth.

In sum, our results suggest that VC funding affects the employment growth rate in the year of VC entry. Beyond this point, there are no clear differences in growth caused by VC funding. Based on this result, it would be interesting to know whether the differences arise gradually in the year of investment, or if it occurs immediately. This is something we take a closer look at in the following subsection.

Employment Growth in the Year of VC Entry

We will now analyze the effect on employment growth in the year of VC entry. As the employment data is based on year-end reporting, we want to see whether the time with VC funding has a significant impact on the employment growth within the year of investment. If the effect is immediate, it should not matter whether target firms receive VC funding in January or December. Then again, if it takes some time before VC entry affects target firms, one should expect VC funding in January to have stronger impact on employment growth than VC funding in December.

To examine these scenarios, we run a separate regression analysis on the target firms, where we only include the observations in the year of investment. As a measure of time with VC funding, we use number of weeks with VC funding in the entry year. As before, we control for year fixed effects, firm fixed effects and firm size. Table 7-5 presents the results from the regression.

As the table reveals, number of weeks with VC funding has no significant impact on employment growth in the year of VC entry. We also try similar regressions, using months and then a dummy[9], rather than weeks with funding. However, the results are more or less the same. Based on these results, we find no evidence to support that the VC effect arises gradually in the investment year. This indicates that the identified employment growth occurs shortly after the time of entry.

[9] The dummy was equal to one if VC funding was between January and June in the entry year, zero otherwise.

7.3 Research Question II: Does the Presence of VC Backed Firms Affect Employment in Competing Firms?

By now, we have seen that VC funding has a positive impact on employment in Norwegian portfolio firms. In this part of the thesis, we analyze whether VC investments also affect the employment growth in other, non-VC backed companies. When VC backed firms grow, do they grow at the expense of others firms within their industry? If VC investments have a substantial negative effect on employment growth in competing firms, it suggests that VC investments lead to a reallocation of labor rather than contributing to net job creation.

To analyze how VC investments affect the employment growth in other firms, we construct a new dataset with annual employment data for each industry[10]. Rather than basing the analysis on our matched sample, we now include all Norwegian firms[11]. Our main indicator of VC presence is the constructed variable *VC activity*, i.e. the number of active target firms that have received VC funding in a given industry for a given year. Further, we also run regressions using a simple dummy for whether or not there are VC funded companies present in the industry. We run panel regressions of the following type:

$$Industry\ employment\ growth_{it} \ = \ \alpha + \beta_1 * VC\ activity_{it} + \gamma * X_{it} + \varepsilon$$

where *i* denotes the industry, t denotes the year, and X_{it} are control variables.

7.3.1 Results

We start by running regressions using *VC activity* as the explanatory variable, and Table 7-6 presents the results. As before, we run several regressions with different model specifications. As a start, we control for average firm age and average total assets in the industry, as well as parent industry group[12]. The regression result indicates that there is a negative relationship between VC investments and employment growth in the related industry. More specifically, a one-unit increase in VC activity is expected to decrease the annual employment growth in the

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[10]As a definition of industry, we use five-digit NACE code.

[11] The employment data includes all Norwegian firms registered in the SNF accounting database. We have excluded the employees in target firms as well as firms backed by other types of private equity to isolate the effect on other firms.

[12] By including parent industry group, we control for variation attributed to overall industry characteristics. For example, if the parent group "Oil and gas" experience a drop in employment growth, the effect will be captured by this control variable.

industry by approximately two percentage points. The same result applies when we use average sales revenues as an additional control variable.

Next, we use the same model specifications, but control for year fixed effects as well. The year dummies will capture variation over time in the employment growth that is not attributed to the other explanatory variables. As Table 7-6 shows, this changes the results. We no longer find evidence of a negative relationship between VC activity and employment growth. The coefficient of VC activity is now significantly reduced and clearly not significant. The change in results indicates that there are significant year effects with respect to employment change. By not controlling for these variations, the previous regressions incorrectly indicate a relationship between VC activity and employment growth.

Further, we change the indicator of VC activity, and use the constructed *VC activity dummy* instead of number of active VC funded companies. This means that we only distinguish between whether or not there are VC backed companies present in the industry, and the aim is to check if there is an overall effect on employment growth. Table 7-6 presents the results from the regression analyses. Again, we try different model specifications, switching between the same control variables as in the first analysis. In short, there are no large differences compared to our first findings.

To sum up the results, we find no reason to claim that employment in competing firms suffers due to the presence of VC backed firms. This indicates that VC investments contribute to net job creation.

7.4 Research Question III: How Do VC Investments Affect Productivity in Portfolio Firms?

From section 7.2, we know that VC funding has a positive impact on the employment level in VC backed firms. However, we are also interested in the productivity of this workforce. Does VC funding also influence the productivity in target firms? Rather than analyzing sales per worker, we define productivity as sales revenues divided by payroll expenses. We prefer this measure, as it reflects the value created in the firm per NOK spent on employment.

Similar to the analyses of employment, we run difference-in-differences regressions to study the VC effect on productivity levels, as well as the effect on annual productivity growth. When analyzing level effects, we run regressions of the following type:

$$Productivity_{it} = \alpha + \beta_1 * Treatment_i + \beta_2 * Treatment_i * After_{it} + \beta_3 * After_{it} + \gamma * X_{it} + \delta_t + \varepsilon$$

In the analysis of growth effects, we change the dependent variable:

$$Productivity\ growth_{it} = \alpha + \beta_1 * Treatment_i + \beta_2 * Treatment_i * After_{it} + \beta_3 * After_{it} + \gamma * X_{it} + \delta_t + \varepsilon$$

Similar to section 7.2, we perform regression analyses with the simple *After*-dummy, in addition to the extended regressions where we divide the dummy into different year variables.

The VC effect on productivity may depend on several different factors. From section 4.1.3, we know that VCs often bring in expertise in the holding period to increase the profitability. This may translate into higher wage levels in target firms, which again will lead to higher payroll expenses. The impact on productivity will depend on whether they manage to increase sales revenues proportionally.

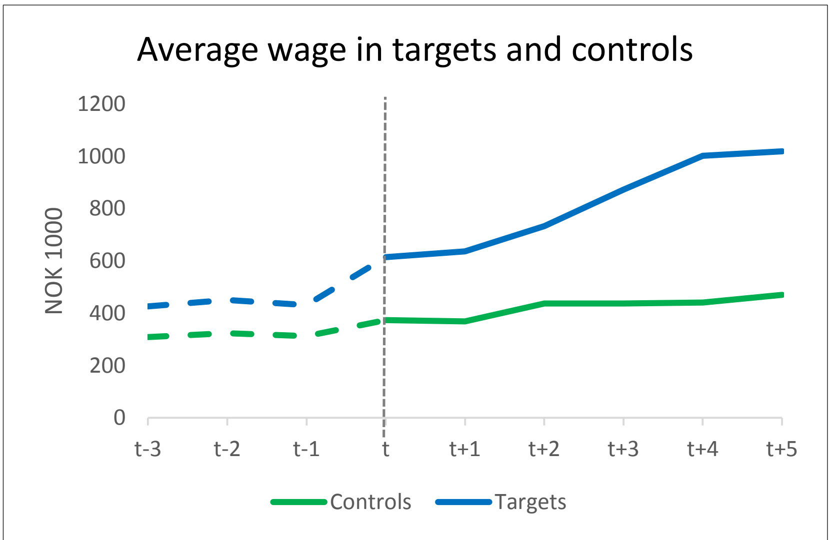
7.4.1 Productivity: Level Effects

Table 7-7 presents the results from the first regression analysis, where we analyze overall differences in the level of productivity between the two groups. *Treatment*After* is still our main variable of interest, as this variable captures the difference-in-differences estimator. Interestingly, we find evidence of a negative relationship between VC funding and productivity. The results suggest that VC funding leads to an overall decrease in the productivity level by 37 percent[13], and the coefficient is significant at a one percent level. It is also worth noting that the *Treatment*-dummy is not statistically significant, which indicates no pre-treatment differences in productivity levels between the two groups.

As for the extended version in Table 7-8, we see that the interaction variables are statistically significant all years after VC entry. The differences arise already in the year of investment, where VC entry decreases the productivity level by 45 percent. After three years, the negative effect is 37 percent. Even though the differences between the two groups are somewhat lower in a longer run, the negative impact of VC entry seems to be consistent.

[13] As before, we use exp(coefficient)-1 to find the percentage effect. The interpretation of the results is based on the first column in the table, marked as (1).

One explanation for why target firms have lower productivity after VC entry could be that it takes time before the new employees reach the productivity level of more experienced employees. As we have identified higher levels of employment in targets starting from the year of VC entry, the lower productivity may indicate that target firms are not able to increase sales proportionally to payroll expenses in the beginning. However, it does not explain why the negative effect is consistent several years after VC entry. This can be explained by higher wages in target firms relative to controls. In general, the wage structure often reflect a firm's ability to attract skilled and productive employees. Interestingly, the average wage per worker is generally higher in target firms relative to controls, as illustrated in Graph 7-4. We also see that the differences increase steadily after VC entry. This development indicates that target firms hire a greater proportion of highly skilled workers after the time of investment. However, it does not seem as if they manage to exploit this to their advantage in terms of increased sales revenues.



Graph 7-4: Average wage in target and control firms before and after VC entry.

7.4.2 Productivity: Growth Effects

We also want to see if the identified differences are evident in a growth perspective. Rather than using productivity levels, we now use annual changes in productivity as the dependent variable. Table 7-9 presents the results from the regression with the simple *After*-dummy. In contrast to the level-analysis, the coefficient for *Treatment*After* is not statistically significant, and we can therefore not claim that VC funding has an overall effect on productivity growth in target firms. However, since we know that the productivity levels differ between the two groups after VC entry, we want to take a closer look at when these differences arise. We will therefore conduct the expanded version of the regression, as it will capture annual growth differences in productivity.

As presented in Table 7-10, we find statistically significant difference-in-differences in productivity growth in the year of VC entry. The size of the coefficient indicates that VC investments lead to a decrease in productivity of 27 percentage points this year. After the year of entry, however, none of the interaction variables are statistically significant. This indicates that the negative growth effect is only temporary, and that the development in productivity growth is similar to control firms beyond the year of VC entry.

In sum, the results from the level and growth analyses suggest that the VC effect on productivity is negative and immediate, and brings the target firms down to a lower level of productivity than the control group. The main reason for the lower productivity levels is higher wages in target firms. Since the growth in productivity does not pick up in the years following VC entry, the level of productivity never recovers to the initial level. The results are robust to changes in control variables.

8. Concluding Remarks

In this final chapter, we provide a summary of our results. We also present limitations of our research, before we suggest some areas for further research.

8.1 Summary

In this thesis, we have analyzed the effect of VC investments on employment and productivity in a sample of 134 Norwegian portfolio companies. The aim was to test whether private VC funding can contribute to job creation as policy makers tend to claim, and to see if there are any VC effects on productivity.

In the first part of the analysis, we perform difference-in-differences analyses, and find that target firms hire more workers after VC entry than the control group. The effect is persistent, and we find no support for a reversal effect. We also find that the employment growth in target firms increases significantly in the year of entry relatively to the control group. This supports findings from similar research papers from other countries, as well as what policy makers tend to claim. However, as a basis for decision-making, we believe that one should look at the total net effect on employment, rather than the isolated employment effect in VC backed companies.

In order to see if the presence of VC funding affects non-VC backed firms, we checked whether the extent of VC activity influences employment in other firms within their industry. We find no reason to claim that employment in other firms suffers due to the presence of VC ownership. This suggests that VC investments lead to net job creation in the Norwegian labor market.

Third, we analyzed whether VC financing has implications for the productivity in target firms. We performed difference-in-differences analyses to compare productivity in targets and controls. We found evidence of lower productivity in targets firms after VC entry, and the negative effect on productivity levels was evident in both a short and long run. Some of these differences can be explained by higher wages in target firms after VC entry, which may reflect that they hire a greater proportion of skilled workers. However, it does not seem like they are able to exploit this in terms of increased sales revenues.

8.2 Limitations

We have limited our analyses to Norwegian portfolio companies funded by Norwegian VCs. There might be other effects caused by the VCs being of foreign origin, but this is not something we look into. We also limit our analyses to first round of VC investments, rather than analyzing possible effects of several rounds.

There are many factors affecting employment growth, and the effect of VC ownership will only be one of many. Even though our findings can provide interesting indications of how VC entries affect employment and productivity, we will not claim that we have controlled for all relevant factors. Hence, more can be done to address causality.

8.3 Suggestions for Further Research

From section 4.1.2, we know that capital can be an accelerator for the business, and that the capital flows in private equity often are characterized by several larger follow-up investments. It would therefore be interesting to analyze the relationship between the size of the initial capital injection and the employment rate. It is also of interest to check how follow-up injections influence employment and productivity in target firms.

Further, we think it would be interesting to do more research related to the identified differences in productivity. We know that there are significant differences in labor costs that arise after VC entry. An approach could be to analyze the VC effect on labor composition. To what extent does VC entry affect the proportion of skilled workers in portfolio firms?

Tables

Descriptive statistics

Table A: Target and Control Firms - Characteristics in Year of Matching

	Target firms				Control firms			
	(1) Average	(2) St.Dev.	(3) Max	(4) Min	(5) Average	(6) St.Dev.	(7) Max	(8) Min
Employees	10	15	85	0	8	15	113	0
Assets	28766	73116	715711	25	20279	93366	1052430	0
Productivity	3.7	12.1	130.2	0.0	5.1	13.2	122.5	-2.4
Sales revenues	21693	105142	1200000	0	13914	30077	219293	0
Payroll expenses	5802	9282	60276	0	4522	10350	79984	-1475

Assets, sales revenues and payroll expenses are in NOK 1000. Productivity measured as sales revenues/payroll expenses.

Table B: Target Firms - Region in Year of Entry

Region	Counties	(1) Frequency	(2) Percent
Østviken	Østfold, Oslo, Akerhus	51	38.06
Innlandet	Hedmark, Oppland	1	0.75
Vestviken	Buskerud, Vestfold, Telemark	5	3.73
Sørlandet	Aust-Agder, Vest-Agder	9	6.72
Vestlandet	Rogaland, Hordaland, Sogn og Fjordane, Møre og Romsdal	35	26.12
Trønderlag	Sør-Trønderlag, Nord-Trønderlag	26	19.40
Nord-Norge	Nordland, Troms, Finnmark	7	5.22
Total		134	100

Table C: Target Firms - Parent Industry Group in Year of Entry

Region	(1) Frequency	(2) Percent
Primary industries	7	5.22
Oil/Gas	2	1.49
Manufacturing industries	24	17.91
Constructions/Energy	2	1.49
Trade	10	7.46
Shipping	0	0
Transport, Tourism	1	0.75
Finance, Insurance	2	1.49
Services/Real estate/Advisors	45	33.58
Health, Care	0	0
Culture, Media	0	0
IT, Telecom	41	30.60
Total	134	100

Table D: Target Firms – Year of VC Entry

Year	(1) Frequency	(2) Percent
1999	1	0.75
2000	0	0
2001	6	4.48
2002	3	2.24
2003	13	9.70
2004	8	5.97
2005	16	11.94
2006	9	6.72
2007	12	8.96
2008	12	8.96
2009	9	6.72
2010	17	12.69
2011	17	12.69
2012	11	8.21
Total	134	100

Regression Results

Table 7-1: Employment Level - Overall Effect of VC Entry

	(1) Employment	(2) Employment	(3) Employment
Treatment	0.0210	0.0097	0.0090
	(0.1603)	(0.1746)	(0.1738)
Treatment*After	0.4975	0.6889	0.6936
	(0.1737)***	(0.1804)***	(0.1803)***
After	-0.2660	-0.2204	-0.1668
	(0.1577)*	(0.1656)	(0.1228)
Year fixed effects	Yes	Yes	No
Firm fixed effects	Yes	No	No
Firm size	Yes	No	No
Observations	3,103	3,410	3,410
R squared	0.1756	0.0485	0.0427

*Standard errors in parenthesis: *significance at ten, ** five, *** one percent. Note: Employment is measured as log(employees+1). Firm fixed effects include region and industry group. Firm size is measured as total assets per December 31 the year before.*

Table 7-2: Employment Level - Effect of VC Entry Over Time

	(1) Employment	(2) Employment	(3) Employment
Treatment	0.0207	0.0097	0.0090
	(0.1606)	(0.1748)	(0.1740)
Treatment*t	0.3762	0.4567	0.4593
	(0.1350)***	(0.1355)***	(0.1348)***
Treatment*(t+1)	0.4533	0.5729	0.5783
	(0.1438)***	(0.1456)***	(0.1456)***
Treatment*(t+2)	0.4751	0.6404	0.6446
	(0.1693)***	(0.1698)***	(0.1699)***
Treatment*(t+3)	0.5098	0.6632	0.6657
	(0.2044)**	(0.2005)***	(0.2009)***
Treatment*(t+4→)	0.5663	0.8406	0.8466
	(0.2437)**	(0.2538)***	(0.2536)***
VC entry time dummies	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No
Firm fixed effects	Yes	No	No
Firm size	Yes	No	No
Observations	3,103	3,410	3,410
R squared	0,1764	0.0512	0.0456

*Standard errors in parenthesis: *significance at ten, ** five, *** one percent. Note: Employment is measured as log(employees+1).Firm fixed effects include region and industry group. Firm size is measured as total assets per December 31 the year before. t represents the year of VC entry for target firms. VC entry time dummies is a collective term for t, (t+1), (t+2), (t+3) and (t+4→).*

Table 7-3: Employment Growth - Overall Effect of VC Entry

	(1) Employment growth	(2) Employment growth	(3) Employment growth
Treatment	0.0946	0.0965	0.0972
	(0.0195)***	(0.0199)***	(0.0195)***
Treatment*After	-0.0083	-0.0220	-0.0209
	(0.0310)	(0.0306)	(0.0297)
After	-0.0740	-0.0649	-0.0756
	(0.0245)***	(0.0240)***	(0.0168)***
Year fixed effects	Yes	Yes	No
Firm fixed effects	Yes	No	No
Firm size	Yes	No	No
Observations	3,046	3,109	3,109
R squared	0.0371	0.0335	0.0178

*Standard errors in parenthesis: *significance at ten, ** five, *** one percent.*
Note: Employment growth is measured as log(employees$_t$ *+1) - log(employees* $_{t-1}$ *+1). Firm fixed effects include region and industry group. Firm size is measured as total assets per December 31 the year before.*

Table 7-4: Employment Growth - Effect of VC Entry Over Time

	(1) Employment growth	(2) Employment growth	(3) Employment growth
Treatment	0.0948	0.0966	0.0972
	(0.0195)***	(0.0199)***	(0.0195)***
Treatment*t	0.1166	0.1199	0.1174
	(0.0675)*	(0.0677)*	(0.0671)*
Treatment*(t+1)	0.0949	0.0925	0.0940
	(0.06320)	(0.0624)	(0.06348)
Treatment*(t+2)	-0.0623	-0.0661	-0.0646
	(0.0705)	(0.0681)	(0.0683)
Treatment*(t+3)	-0.0875	-0.0766	-0.0744
	(0.0609)	(0.0599)	(0.0589)
Treatment*(t+4→)	-0.0638	-0.0890	-0.0866
	(0.0426)	(0.0414)**	(0.0409)**
VC entry time dummies	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No
Firm fixed effects	Yes	No	No
Firm size	Yes	No	No
Observations	3,046	3,109	3,109
R squared	0.0450	0.0426	0.0268

*Standard errors in parenthesis: *significance at ten, ** five, *** one percent.*
Note: Employment growth is measured as log(employees$_t$ +1) - log(employees $_{t-1}$+1). Firm fixed effects include region and industry group. Firm size is measured as total assets per December 31 the year before. t represents the year of VC entry for target firms. VC entry time dummies is a collective term for t, (t+1), (t+2), (t+3) and (t+4→).

Table 7-5: Effect of VC in the Year of Entry

	(1) Employment growth	(2) Employment growth	(3) Employment growth
Weeks with VC	-0.0051		
	(0.0036)		
Months with VC		-0.0245	
		(0.0160)	
Between January and June			-0.0698
			(0.1053)
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Firm size	Yes	Yes	Yes
Observations	134	134	134
R squared	0.3275	0.3296	0.3175

*Standard errors in parenthesis: *significance at ten, ** five, *** one percent.*
Note: Employment growth is measured as log(employees$_t$ +1) - log(employees$_{t-1}$+1). Weeks with VC is the number of weeks with VC funding in the year of entry. Months with VC is the number of months with VC funding in the year of entry. Between January and June is a dummy equal to one if VC entry was between January and June in the year of entry, zero otherwise. Firm fixed effects include region and industry group. Firm size is measured as total assets per December 31 the year before.

Table 7-6: Effect of VC Activity on Other Firms

	(1) Industry employment growth	(2) Industry employment growth	(3) Industry employment growth	(4) Industry employment growth	(5) Industry employment growth	(6) Industry employment growth
VC activity	-0.0232	-0.0232	-0.0080	-	-	-
	(0.0116)**	(0.0116)**	(0.0114)			
VC activity dummy	-	-	-	-0.0813	-0.0809	-0.0052
				(0.0396)**	(0.0396)**	(0.0394)
Average firm age	Yes	Yes	Yes	Yes	Yes	Yes
Average assets	Yes	Yes	Yes	Yes	Yes	Yes
Parent industry group	Yes	Yes	Yes	Yes	Yes	Yes
Average sales revenues	No	Yes	Yes	No	Yes	Yes
Year fixed effects	No	No	Yes	No	No	Yes
Observations	12,486	12,472	12,472	12,486	12,472	12,472
R squared	0.0162	0.0167	0.0003	0.0162	0.0167	0.0003

*Standard errors in parenthesis: *significance at ten, ** five, *** one percent.*
Note: Industry employment growth is measured as log(employees$_t$ +1) - log(employees$_{t-1}$ +1) for each five-digit industry code. Average assets and average sales revenues are both measured per December 31 the year before.

Table 7-7: Productivity Level - Overall Effect of VC Entry

	(1) Productivity	(2) Productivity	(3) Productivity
Treatment	-0.1604	-0.2007	-0.1940
	(0.1199)	(0.1391)	(0.1388)
Treatment*After	-0.4571	-0.4703	-0.4791
	(0.1379)***	(0.1542)***	(0.1528)***
After	0.0279	0.0665	0.0416
	(0.0893)	(0.1054)	(0.0901)
Year fixed effects	Yes	Yes	No
Firm fixed effects	Yes	No	No
Firm size	Yes	No	No
Observations	2,513	2,678	2,678
R squared	0.1791	0.0569	0.0480

*Standard errors in parenthesis: *significance at ten, ** five, *** one percent. Note: Productivity is measured as log(sales revenues/payroll expenses). Firm fixed effects include region and industry group. Firm size is measured as total assets per December 31 the year before.*

Table 7-8: Productivity Level - Effect of VC Entry Over Time

	(1) Productivity	(2) Productivity	(3) Productivity
Treatment	-0.1604	-0.2007	-0.1940
	(0.1202)	(0.1394)	(0.1390)
Treatment*t	-0.5892	-0.5442	-0.5538
	(0.1465)***	(0.1546)***	(0.1549)***
Treatment*(t+1)	-0.4174	-0.4339	-0.4384
	(0.1734)**	(0.1843)**	(0.1833)**
Treatment*(t+2)	-0.3814	-0.3876	-0.3992
	(0.1594)**	(0.1673)**	(0.1656)**
Treatment*(t+3)	-0.4620	-0.4676	-0.4709
	(0.2166)**	(0.2217)**	(0.2189)**
Treatment*(t+4→)	-0.4376	-0.4866	-0.4953
	(0.1927)**	(0.2104)**	(0.2106)**
VC entry time dummies	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No
Firm fixed effects	Yes	No	No
Firm size	Yes	No	No
Observations	2,513	2,678	2,678
R squared	0.1805	0.0607	0.0511

*Standard errors in parenthesis: *significance at ten, ** five, *** one percent.*
Note: Productivity is measured as log(sales revenues/payroll expenses). Firm fixed effects include region and industry group. Firm size is measured as total assets per December 31 the year before.t represents the year of VC entry for target firms. VC entry time dummies is a collective term for t, (t+1), (t+2), (t+3) and (t+4→).

Table 7-9: Productivity Growth - Overall Effect of VC Entry

	(1) Productivity growth	(2) Productivity growth	(3) Productivity growth
Treatment	0.0608	0.0489	0.0490
	(0.0441)	(0.0412)	(0.0413)
Treatment*After	-0.0378	-0.0361	-0.0366
	(0.0618)	(0.0605)	(0.0608)
After	0.0352	0.0316	0.0421
	(0.0442)	(0.0431)	(0.0228)
Year fixed effects	Yes	Yes	No
Firm fixed effects	Yes	No	No
Firm size	Yes	No	No
Observations	2,336	2,363	2,363
R squared	0.0140	0.0095	0.0006

*Standard errors in parenthesis: *significance at ten, ** five, *** one percent. Note: Productivity growth is measured as log(sales revenues$_t$ /payroll expenses$_t$) - log(sales revenues$_{t-1}$ /payroll expenses$_{t-1}$). Firm fixed effects include region and industry group. Firm size is measured as total assets per December 31 the year before.*

Table 7-10: Productivity Growth - Effect of VC Entry Over Time

	(1) Productivity growth	(2) Productivity growth	(3) Productivity growth
Treatment	0.0606	0.0488	0.0491
	(0.0442)	(0.0413)	(0.0414)
Treatment*t	-0.3206	-0.3151	-0.3174
	(0.1461)**	(0.1443)**	(0.1447)**
Treatment*(t+1)	0.1344	0.1243	0.1291
	(0.1085)	(0.1103)	(0.1110)
Treatment*(t+2)	-0.0751	-0.0691	-0.0732
	(0.1420)	(0.1381)	(0.1385)
Treatment*(t+3)	0.0661	0.0520	0.0489
	(0.1764)	(0.1722)	(0.1726)
Treatment*(t+4→)	-0.0093	-0.0073	-0.0071
	(0.0685)	(0.0643)	(0.0639)
VC entry time dummies	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No
Firm fixed effects	Yes	No	No
Firm size	Yes	No	No
Observations	2,336	2,363	2,363
R squared	0.0195	0.0147	0.0055

*Standard errors in parenthesis: *significance at ten, ** five, *** one percent. Note: Productivity is measured as log(sales revenues$_t$ /payroll expenses$_t$) - log(sales revenues$_{t-1}$ /payroll expenses$_{t-1}$). Firm fixed effects include region and industry group. Firm size is measured as total assets per December 31 the year before. t represents the year of VC entry for target firms. VC entry time dummies is a collective term for t, (t+1), (t+2), (t+3) and (t+4→).*

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