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Major Layoffs' Impact on Venture Capital Activity

- *A study on how Ericsson and Nokia's layoffs affected the Nordic venture capital activity.*

Gard Elias Kolbeinsen & Frederic Fjogstad Willassen

Supervisor: Carsten Bienz

Master thesis in Finance

Abstract

This paper investigates the relationship between company-related shocks and the Nordic private equity and venture capital industry. We investigate the consequences from Ericsson and Nokia's major layoffs in 2002 and 2012 and present some extraordinary and very interesting results. Several different analyses have been conducted, both at an aggregated level and at deeper levels. This includes a thorough investigation of the amounts invested and number of companies invested in after the shocks. We use Sweden, Finland, Denmark and Norway as the targeted countries of interest, giving the analysis credibility in respect of a shock's impact in the Nordics. Among other findings, we present results that indicate that the number of companies invested in, in the high-tech sector, increased in both Sweden and Finland, compared to Denmark after such a shock. They also suggest that the increase in the number of companies invested in was larger in the high-tech sector compared to other sectors. This also indicates that a major layoff in a specific industry will boost the start-up activity within the same industry. In addition, there appears to be an unchanged risk aversion among investors, as the invested amount appears to be unaffected after a major layoff.

These results can give an interpretation that the number of companies invested in could increase in Norway after the nation's current difficulties. With the results presented, we expect that the number of companies invested in, in energy-related industries, will be greater in Norway compared to other Nordic countries.

Preface

This thesis was written as a part of our master of science in Economics and Business Administration at the Norwegian School of Economics (NHH). We are both majoring in Finance and have a sincere interest in corporate finance, M&A, IPO's and private equity. It was important for us to choose a topic that we are both interested in, at the same time as it covered our major. The private equity and venture capital industry is interesting but somewhat closed. Unlike publicly traded companies, the available information about portfolio companies and transactions within private equity and venture capital is limited. Many different studies have been conducted regarding the industry, but there are still many unanswered questions. We started to investigate potential problems for our thesis early summer 2015 and had regularly contact with the Norwegian private equity and venture capital association and other main players in the Norwegian private equity industry. After numerous emails, a discussion with Joachim Hoegh-Krohn in Argentum and our supervisor, Carsten Bienz, we believe that we have identified a very interesting research question. The investigated topic in this thesis has, to our knowledge, not been investigated before and will possibly give the industry new and interesting information.

Gathering the necessary data for the thesis has been a demanding process involving email correspondence with Swedish, Norwegian, Danish and Finish private equity and venture capital associations, central banks and central statistic agencies. We also had telephone contact with a private equity database in Seattle, US, to find the best possible data source.

We would like to thank the following for useful insight concerning a potential problem for our master thesis and gathering necessary data:

- Carsten Bienz, supervisor and associate professor, NHH
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1. Introduction

There is currently a discussion in Norway on how the government can increase the start-up activity in the country. Both politicians and representatives from the Norwegian venture capital environment seem to agree that the problem is related to the amount of capital available for entrepreneurs. The Norwegian government has therefore proposed to increase the appropriations to Innovation Norway with NOK 100 million (Regjeringen, 2015). The question is, however, if this is the correct solution to the problem.

One would expect that entrepreneurs in Norway have access to the same amount of private capital as the rest of the Nordics (excluded Iceland), but the number of Norwegian companies invested in, in seed & start-up has been historically lower than both Sweden and Finland the last 18 years (EVCA). The question is; can the exogenous variation between the countries be explained by the lack of capital, or are there other factors affecting the start-up activity?

In an article published by BBC on January 30, 2015, we can read that Nokia's fall in 2012 has led to "an explosion of start-ups" in Finland (BBC, 2015). Similar articles are published regarding the start-up activity in Sweden after Ericsson's fall in the beginning of the millennium. These articles imply that venture capital activity does not entirely depend on the access of capital but in addition, the access to human capital.

The majority of existing literature on the determinants of venture capital activity focuses on the supply side of venture capital. Gompers and Lerner (1999) studied venture capital fundraising using macroeconomic parameters like GDP growth and capital market growth, while Marti and Balboa (2001) found that divestments had a significant effect on the funded amount. There have not been many studies regarding the effect of entrepreneurial environment, but Romain & Potterie (2004) introduced this as a possible determinant. They concluded that the environment for entrepreneurs has a significant effect on the venture capital activity. Felix, Gulamhussen & Pires (2007) later presented a similar independent variable as they implemented "The total entrepreneurial activity index" (TEA). Their results, however, showed no significance in neither total nor early stage investments.

In this paper, we investigate the determinants of the venture capital activity in the Nordics from a new perspective. We examine if the mentioned exogenous variation between the countries can be explained by human capital availability, and do this by investigating if a sudden increase in available human capital will have a positive effect.

We are therefore dependent on distinguishing between the different countries' historical access to human capital. Sweden, Finland and Norway have had a sector attracting a high percentage of the countries' knowledge, where Sweden and Finland have attained a large portion of their knowledge within the high-tech[1]sector, while Norway's largest portion of human capital is related to the energy sector. Denmark has, opposed to its neighbors, no specific industry attracting the nation's work force.

Since the early 2000s, Sweden's Ericsson and Finland's Nokia faced several difficulties and obstacles in their operations. The companies experienced billions in losses, forcing them to lay off several thousand employees. Norway and Denmark have historically not experienced the same magnitude of increased available human capital.

The shocks[2] in Sweden and Finland occurred in the high-tech sector, which is why it is reasonable to expect that the human capital released in these countries would start up companies within the same sector. A potential increased venture capital activity in these countries should therefore be a consequence of higher activity in the high-tech sector.

We use Ericsson and Nokia because of their similarities in size and in sector, and examine the effect of the shocks on the countries' venture capital activity. We use the EVCA[3] database (EVCA, 2015) to look at the activity between 1999 and 2014 on four Nordic countries.

Previous literature focuses on aggregated fundraising while we look deeper into the question regarding the determinants. We look at the demand side and use natural occurring shocks to test our hypotheses. Our analyses target the problem both at an aggregated and at a sector level, which enables us to measure the effect of a major layoff on different investment stages and if a specific

[1] The high-tech industry includes communications and data & consumer electronics.
[2] A shock is characterized by a major layoff in a specific industry, or even a specific company
[3] European Venture Capital and Private Equity Association

sector will be more affected than others. The activity is analyzed on three different levels, all venture, seed & start-up and at the sector level.

We compute our analyses concerning the amount invested and the number of companies invested in. This is because we expect a higher venture capital activity after the company-related shocks, but the increased activity will not necessarily appear in the amount invested. The reasoning behind this is that an increase in available human capital can result in higher diversification as venture capitalists will be able to spread their investments on a greater number of companies. It is also reasonable to assume that investors can be risk averse, which might result in unchanged amounts invested or even a decrease in the invested amount.

A difference in differences inspired panel data approach with a fixed effects and a first differences framework is used. We use a dummy variable for the years following a shock, and test if it has a statistically significant effect on the difference in venture capital activity in the Nordics. The differences in the activity are calculated using Denmark as a reference. Several non-lagged and lagged independent variables, which have shown significance in previous studies, are included (Gompers and Lerner 1999).

Our analyses indicate that the aggregated venture capital activity might be affected by a shock, as the number of companies invested in, in venture capital seems to increase. When measuring the effect in seed and start-up we see, however, that it has a negative effect. The results suggest that the shock causes an average annual decrease in the difference of 71-74 companies invested in, within the shock window. Our analyses between the shock-affected countries' high-tech sector and Denmark's high-tech sector indicate an average annual increase of companies invested in between 40 and 55. This is consistent with our initial hypothesis that the released human capital will tend to return to the same sector.

In addition, we can present very interesting results from several regressions concerning the differences between the shock-affected sector and other sectors. The differences between sectors are also analyzed with Denmark used as a reference. We use the sector analyses to test if an increase in the shock-affected sector is because of an average change in total venture capital activity, or if the sector experiences a higher impact than others do. Life science is chosen as the main control sector as it is the most similar to high-tech regarding size and other characteristics such as R&D importance. Finally, we include two other sectors as robustness checks.

The results from the sector analyses imply the same as the previous. The difference in differences analyses between high-tech and life science indicate a significant average annual increase of companies invested in after the shocks. The results suggest that the positive effect was between 32 and 74 companies invested in. When comparing the high-tech sector to the business & industrial products and the energy & environment sectors, the results are consistent, indicating an average annual increase of 35 to 50, and 39 to 53 companies respectively. This supports our hypothesis that a major layoff will have a positive effect on the affected sector relative to others.

The shock does, however, show little to no significant effect on the amount invested, which is corresponding to what Felix, Gulamhussen & Pires (2007) found when they used TEA in their study, and supports our previous statement about a shock's impact.

The results presented in this report are very interesting as it may predict an increase in the number of companies invested in, in Norway for the coming years. The increase will not necessarily be a result of the increased appropriations from the government, but rather an increase in the available human capital from the energy industry.

Innovation Norway stated in the summer of 2015 that it would be too early to conclude if the major layoffs in Norway have an effect on the nation's start-up activity. They could, however, see a significant and positive tendency in the number of people wanting to start up their own business. The tendency was, not surprisingly, strongest where the oil crisis has hit the hardest. Rogaland, Norway's leading oil county, had a tripling in the number of applications for start-ups in respect of the summer in 2014 (TU, 2015).

1.2 Key Concepts and Definitions

Venture capital is, as most other products, determined by demand and supply (Gompers & Lerner 1999) and it is the drivers behind the two that ultimately determine the total activity. The supply factor is the different investors (pension funds, university endowments etc.), and their willingness to make capital available for venture. The demand side is the desire for entrepreneurs to attract venture capital from the market, as these entrepreneurs can find it difficult to acquire this elsewhere. It is important to note that the entrepreneurs need to have the ability to obtain a certain rate of return for the investors. Entrepreneurs without the ability to achieve the desired return are not included as part of the demand. When investigating the effect of a major layoff on venture capital activity, it is therefore important that the increased human capital is able to achieve this required return to affect the demand for venture capital.

The total activity is calculated as the equilibrium between the supply and demand. There are different factors affecting the two sides; for example, a higher rate of return on venture capital investments will increase the supply of capital, while a higher loan rate can increase the demand as more entrepreneurs will seek for venture capital instead. In this thesis, our focus is on determining if a large increase in available entrepreneurs (human capital) will affect the demand for venture capital.

1.3 Limitations

The analyses are based on a dataset on the Nordic countries excluding Iceland. Iceland's venture capital industry is too small to be included, and the country differs from the other Nordic countries. The dataset received from the EVCA does not contain the number of companies invested in before 1997, making longer analyses impossible. The most optimal when investigating shocks and its effect on the venture capital industry is to have the exact date, size and locations/regions of the companies' layoffs. Numerous emails have been sent to Ericsson and Nokia, but the companies have not replied. The basis for the shocks has therefore been the annual reports and, to some extent, public statements, resulting in that the analyses are done on a yearly basis. Since there are no previous studies done on the exact topic, we also use our own assumptions when building the models for the empirical analyses.

2. Data Description

In this chapter, we will explain why we use the Nordic countries as a basis of comparison and the period used in the analyses. We will then define the dependent and the independent variables before we finally define the shocks and the shock windows.

2.1 The Choice of Countries

The Nordic countries are almost identical regarding culture, political system, economic freedom and in terms of financial markets, which makes it appropriate to use them as a basis of comparison.

Culture. The culture in the Nordics can be defined as "chilled out" and people from Scandinavia are often described as boring. The most important aspect of the Nordic culture concerning this study is, however, their high level of education. The four countries are all on the top 25 list (OECD) concerning the percentage share of the population aged 25-34 that has attained a tertiary level of education. Highest on the list is Norway, located on 7th place, followed by Sweden in 10th, Denmark in 18th and Finland on 23rd (OECD, 2013). Common for Norway, Sweden and Finland is that they, in addition to high education levels, have had or currently have an sector or even a specific company attracting a large portion of the nation's knowledge. Such knowledge magnets will be Norway's energy sector, Sweden's Ericsson and Finland's Nokia. These properties have been crucial when choosing our data sample. Denmark does not have any specific industry or company that attract the nation's most knowledgeable in the same magnitude as its neighbors and is included in the sample as a reference.

Tax and the Nordic model. The Nordics have been a synonym with socialism, but this relation has changed substantially the last two decades. In 1993, Sweden spent as much as 67% of its total GDP on the public and citizens were forced to pay more than 100 percent in income taxes (The Economist, 2013). The countries started to lose their global competitiveness, which resulted in a change in course. Political systems became more liberalistic, resulting in both lower corporate taxes and public spending. The corporate tax rates vary between 22% and 27% and are in fact much lower than in the United States, which varies between 30% and 35% (Deloitte, 2015). The Nordic social democracy represents both a welfare state and free market capitalism with high global competitiveness. The welfare state aims to enrich the individual autonomy and to promote social mobility (The Economist b, 2013). The welfare state is also identified with each country's different labor organizations, where employees and employers discuss different aspects of the working environment. The countries give their citizens incentives for business with both private ownership and free trade. Their economies are dominated by high transparency, very low level of corruption and a very high degree of economic freedom.

Economic freedom. When talking about the economic freedom, we use the index of economic freedom from the heritage as a reference. The individual country's total score on the index comprises of 11 sublevels of different aspects of economic freedom. These sublevels consist of property rights, freedom from corruption, government spending, fiscal, business, labor, monetary, trade, investment and financial freedom. Denmark receives the highest overall score with 76.3 followed by Finland with 73.4, Sweden with 72.7 and Norway with 71.8 (Heritage, 2015). The countries have historically had approximately the same level of economic freedom, which also suggest that it would be appropriate to use them as a basis of comparison. Previous studies surrounding the venture capital activity use a larger selection of countries and have been dependent on the index as an independent variable. By using the Scandinavian countries, we are able to measure the effect of other variables in a better manner, as we know that the economic surroundings are alike.

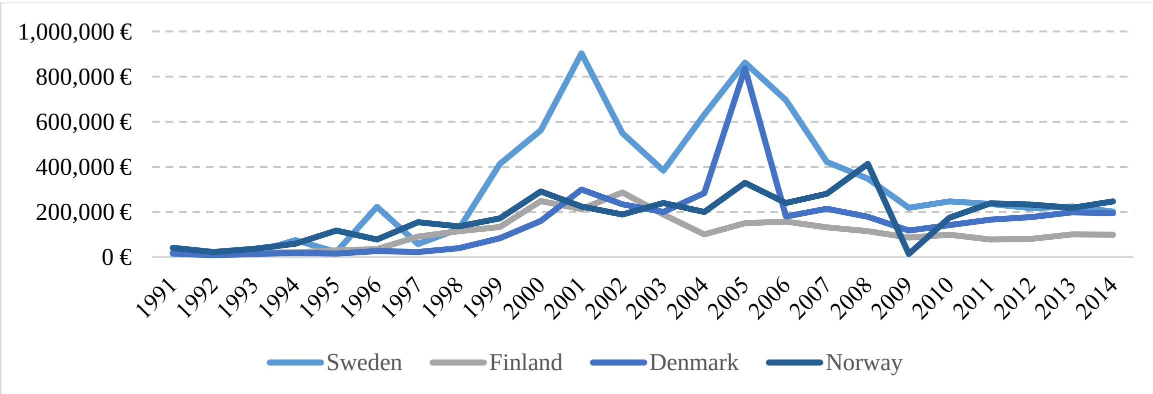
Financial markets. Gilson and Black (1999) studied the American venture capital industry versus the industry in Germany and Japan. Their study showed that it is crucial for a venture capital industry to have efficient and well-developed stock markets that permit exits. The financial markets in the Nordic countries are efficient and well-functioning, permitting exits.

Using the Nordic countries as a basis of comparison will ensure that the analyses in this report are based on similar environments and give the results as high credibility as possible.

2.2 Sample Selection

To use the most appropriate sample for our analyses, we start by identifying the maturation process of the Nordic venture capital industry.

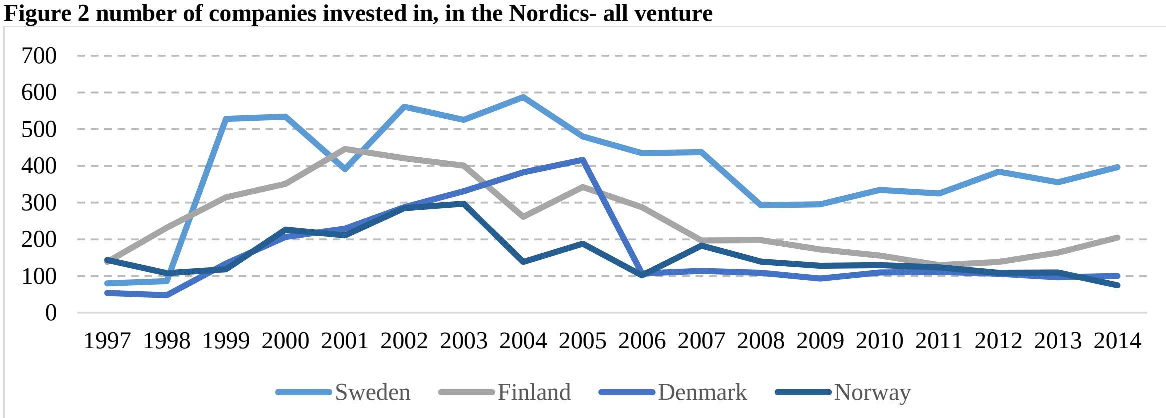
Figure 1 all amount invested in total venture in the Nordics, all numbers in EUR x 1000



Data from EVCA

The venture capital industry in Europe experienced a significant increase in the amount invested in the period 1998-2000. The invested amount in seed, start-up and in later stage venture increased 230%, from approx. EUR 6 billion in 1998 to approx. 20 billion in 2000. One of the biggest contributors to this magnificent growth was Sweden. Sweden's invested amount in total venture increased from EUR 124 million in 1998 to 902.5 million in 2001 (EVCA, 2015).

Figure 2 number of companies invested in, in the Nordics- all venture



Data from EVCA

It was not only the amount invested that increased, but also the number of companies invested in. The number of companies invested in, in Europe in 1998, was 4636, whilst in 2000 the number was 9182. Sweden also reflects this increase, with its 86 companies in 1998 and 534 companies in 2000. It is somewhat uncertain if this increase was a result of a maturation process of the European venture capital industry, the IT-boom surrounding the millennium or simply an increased number of members to EVCA.

EVCA’s datasets have various lengths stretching from 1989 to 2014. Information regarding invested amounts goes back to the early 90s while the number of companies invested in stretches back to 1997. The activity in the early and mid-90s was rather moderate, and the Nordic part of the industry was not mature at this stage. We have therefore concluded to run our analyses from 1999 to 2014. This will also make it easier to compare our results from the amount invested and the number of companies invested in.

After a thorough investigation, where we found the exact month of approx. 2000 transactions, we concluded that yearly data would be the most appropriate for the analyses. The reason for this is simply that it is difficult to be certain whether public announcements reflect the actual time of each transaction. Running our analyses on such an uncertain data collection would make the entire analysis unreliable. We assume that EVCA has the most reliable database on venture capital transactions in Europe, which is why we have chosen to run the analyses on a yearly basis with data from the EVCA.

2.3 Choice of Dependent Variables

Several dependent variables have been included in this study. This is done to get a broader understanding of the effect from a shock and give a broader basis for the conclusion.

Number of companies invested in, all venture capital. The total number of companies invested in, in all venture capital includes seed investments, start-up and later stage venture. This is categorized as the most aggregated level of our analysis.

Number of companies invested in, seed and start-up. To get a deeper understanding of how a shock affects the number of companies invested in, we remove the later stage venture from the analysis. It is logical to assume that later stage investments are not affected to the same degree as seed and start-up.

Number of companies invested in, high-tech. As our focus is on the shock-affected sector (high-tech), we separate out these investments from the rest. By doing this, we get a more detailed analysis and are able to measure the effect on a sector level. A consequence of doing a narrower analysis is that the data does not distinguish the venture capital investments from buyouts. This is further addressed in chapter 4.1.

Amount invested. In addition to the number of companies invested in, we measure the effect on the amount invested. The reason behind this is that the number of companies invested in and the amount invested may be differently affected by the determinants (including the shock). This could for example be a financial crisis, where the amount invested is more affected than the number of companies invested in. The analyses surrounding the amount invested are similarly divided into all venture capital, seed and start-up and the high-tech sector.

The difference between sectors. Finally, we divide investments into different sectors, where we investigate the effect on the difference between high-tech and several other sectors. By doing this, we study if changes in the venture capital activity are higher in certain sectors. The sector analyses are done similarly as the above, including number of companies invested in, and the amount invested.

2.4 Choice of Independent Variables

There is as mentioned no previous research on the correlation between company-related shocks and the venture capital activity. There has however been conducted various academic research on the determinants of venture capital fundraising. These studies are used when choosing the most suitable independent variables for our analyses.

We include the yield on a 10-year government bond, annual market growth, annual average adjusted unemployment rate, annual IPO divestments, R&D expenditures in the percentage of GDP and annual GDP per capita growth. Some previous researchers use, as mentioned, the economic freedom index as an independent variable, but this is not necessary for our analysis due to the Scandinavian countries' similarity.

The yield on a 10-year government bond (National Banks, 2015). This independent variable can affect our dependent variables in two ways. A lower yield would give incentives to investors to invest in venture capital, as they will get a higher return than investing in bonds. A higher yield can cause difficulties acquiring debt, resulting in a higher demand for venture capital. The overall result will depend on the supply and demand. The yield has previously proven to have a significant effect on the activity in 16 OECD countries (Romain and De La Potterie, 2004).

Market growth (NASDAQ). The market growth is calculated from different stock indices from each individual country. The purpose for this variable is to measure the different nation's economic situation. The OMXC20 for Denmark, the OMXS30 for Sweden, OMX Helsinki 25 EXP for Finland and the OSEBX for Norway (Yahoo Finance, 2015) are used. We use the average growth of the respective indices to reflect events with major influence on the economy, such as the IT-bubble surrounding the millennium and the sub-prime crisis in 2008.

Adjusted Unemployment (World Bank a, 2015). This variable can, similar to the bond yield, potentially influence the venture capital activity in two ways. A decrease in the unemployment rate can indicate that the economy goes well, giving investors a belief that it is "safe" to invest. Increasing unemployment rates will indicate that there are potentially more people willing to start up a new company, increasing the need of venture capital. Cherif and Gazdar (2011) found that unemployment rates had a strong negative impact on venture capital investments in Europe.

IPO divestments (EVCA, 2015). Private equity firms that exit its portfolio companies realize a return, which is often a profit. IPO divestments will therefore be a measure of success, trigging more investors to join the capital base. Marti and Balboa (2001) presented results indicating that divestments were important for the funded amount. IPO divestments are characterized as the number of annual IPO divestments from private equity/venture capital firms within a country.

R&D expenditures in the percentage of GDP (OECD, 2014). This variable reflects the companies' willingness to invest in R&D. It can affect both the invested amount and the number of companies invested in, in two ways. Higher R&D expenditures would indicate that companies are doing well, not only focusing on the present but also on future income. This may reflect the condition of the venture capital industry and result in more investments. A decrease in R&D expenditures will on the other hand often lead to layoffs in R&D departments, giving employees the chance to fulfill their own ideas. Increased R&D will also increase the overall knowledge in the country, making the probability for more innovation/start-ups higher. Gompers and Lerner (1998) found that R&D has a positive correlation with venture capital activity.

GDP per capita growth (World Bank b, 2015). GDP growth is also implemented to reflect the economic condition in the countries. The variable is expected to be positively correlated with the amount invested and the number of companies invested in. Romain & De La Potterie (2004), Marti & Balboa (2001) and Gompers & Lerner (1998) have all used the GDP growth as an independent variable.

2.5 Choice of Shock

The two countries in our data sample that have experienced a major shock are Sweden and Finland. They have tremendous experience and expertise in the high-tech segments, including tele and data sciences, which is reflected in the total amount invested in venture capital and the number of start-ups in the two countries. The shocks used in this study are shocks from Ericsson and Nokia respectively, meaning that both occurred in the high-tech sector. Ericsson and Nokia have been two major companies, with hundreds of thousands employees globally. Saab's different shocks in Sweden were also considered, but the probability that employees in Saab start their own high-tech company is significantly smaller.

To locate the shocks, we use both the size of the companies' loss and the number of employees laid off. Ericsson's biggest loss was in 2001, where the company had a net income of SEK -21.3billion (Ericsson, 2001 and 2002). The company's number of employees the same year went down from 105.000 to 85.000, a reduction of 19%. The total number of employees in Sweden, however, went up by 2000 the same year. In 2002, the total number of employees in Sweden was reduced from 39.000 to 30.000, a significant reduction in the work force, which is exactly what we want to include in an analysis like this. Ericsson's R&D expenses the same year went from SEK 46 billion to SEK 33 billion (-28%), which makes it reasonable to assume that a large part of the employees laid off came from the R&D department. The start of Ericsson's shock is therefore set to 2002, a year after their biggest loss.

In Finland, Nokia had their biggest loss in 2011, where they experienced a loss of EUR -1.5billion (Nokia, 2011 and 2012). The total number of employees on December 31, 2011, was approx. 130.000, 2000 less than the year before. In the end of 2012, the total number of employees had fallen to approx. 98.000, a reduction of 32.000 globally. Nokia does, however, not mention how many of the employees that were located in Finland, but New York Times announced in 2012 that at least 3700 would lose their jobs (NY Times, 2012). Nokia teamed up with Windows in 2011, and has reduced the workforce ever since. Nokia's R&D expenditures were in 2012 reduced with EUR 802million, or approximately 15%. The start of Nokia's shock is therefore set to 2012.

2.6 Choice of Shock Window

It is reasonable to assume that the released human capital from the two tech-companies either has found a new employer or started a new company within three years. The shock windows start one year after the two companies' biggest loss and the same year as a significant reduction in domestic work force. The time for each shock has been set to three years. The shock windows are therefore 2002-2004 and 2012-2014 for Sweden and Finland respectively. It is worth mentioning that the two companies reduce their labor force regularly, but the two shocks included in this analysis are the major ones. The other layoffs in the respective countries have been in the hundreds, which will not be sufficient to affect any of the dependent variables significantly.

3. Empirical Analyses and Results

The chapter is divided into several parts, where we first look at appropriate empirical frameworks that are used when building the model for our analysis. We then define our model and investigate the pre-regression findings. Finally, we present several analyses where we examine the differences between the venture capital activity between countries and sectors.

Our examination requires repeated observations on the same cross section, on each of the Nordic countries, making panel data analyses the most appropriate. Panel data will due to an increased number of observations, give a greater precision in estimation. The reason why we get a higher precision is that we will be able to pool different observations for each country together. There is, however, no free lunch, meaning that there are some implications when using a panel data analysis. Several panel data frameworks can be applied to cope with these. (Wooldridge, 2012).

The “easiest” and most restrictive panel data approach is the pooled OLS model. The model collects all of the observations together in a pool, using all the observations as a big cross-section. By doing this, the model will ignore time-invariant country-specific effects, which might give coefficients without any economic meaning. Pooled OLS assumes homoscedasticity, normality and no serial correlation between the independent variables and the composite error (Wooldridge, 2012). Our implemented tests show that a pooled OLS will not be appropriate for the necessary analyses (chapter 4.2).

Each country included in the dataset has individual specific effects, which are assumed fixed. The individual specific effects correlate with the independent variables, which is why we base our model on a fixed effects and a first differences framework.

The theory behind the panel data frameworks is described in the next pages, while the choice of the correct empirical framework is addressed more in detail, in chapter 4,2.

3.1 Fixed Effects Model

When using a fixed effects model the intuition is to measure the effect from time variant variables. The fixed effects model is also called the within estimator, meaning that the model considers each country's individual fixed variables (Dougherty, 2011). In the model, the quantile of each variable within each country will be fixed and not random. This is the opposite from a random effects model, where one will assume that the quantile of each variable is determined by chance. An important assumption is that the fixed effects model assumes correlation between each country's specific effect and the independent variables.

The premise behind the framework is that omitted variables will be fixed or constant. The model removes the omitted variable bias by measuring variation over time. To do this, the values and the effect of each variable must be time constant. The fixed effects model also control for omitted variables by using each country as their own controls (Williams, 2015).

The model uses differences within the countries, ignoring variation between them. If the independent variables differ significantly between countries and have a low individual variance, the results from a fixed effects model will be imprecise with large standard errors (Williams, 2015). The independent variables included in this study do not have a small within variation, confirming that a fixed effects estimation is appropriate.

The mathematical expression for a linear unobserved effects model is as follows (Wooldridge, 2012):

1) $Y_{i,t} = X_{i,t}\beta + \alpha_i + u_{i,t} \quad for \quad t = 1 \; and \; i = 1, \ldots., N$

where $Y_{i,t}$ is a dependent variable, $X_{i,t}$ an independent variable, α_i the unobserved time-invariant individual effect and $u_{i,t}$ the idiosyncratic error term.

In a fixed effects model, the unobserved time-invariant individual effect is assumed correlated to the independent variables. The unobserved time-invariant individual effect is difficult to control, but by assuming that this will be constant over time, we are able to exclude this through a "within transformation":

2) $Y_{i,t} - \overline{Y_{\iota,t}} = \beta(X_{i,t} - \overline{X_{\iota,t}}) + (\alpha_i - \overline{\alpha}_\iota) + (u_{i,t} - \overline{u_{\iota,t}})$ where $\alpha_i = \overline{\alpha}_\iota$, resulting in

3) $\ddot{Y}_{\iota,t} = \beta\ddot{X}_{\iota,t} + \ddot{u}_{i,t}$

If this equation satisfies the classical linear model assumptions, the fixed effects estimator can, according to Wooldridge, be found through an OLS regression of $\ddot{Y}$ and $\ddot{X}$.

Even if the α_i is allowed to be correlated with the independent variables, the model assumes strict exogeneity. Strict exogeneity excludes the possibility that present changes in the error term $u_{i,t}$ can cause future changes in the independent variable $X_{i,t}$. Meaning that the error term is uncorrelated with past and future shocks to Y (Wooldridge, 2012).

The model has, in addition, these assumptions:
I) The countries included in the analyses are functionally identical.
II) The sample in the cross section dimension is random.
III) The idiosyncratic errors are uncorrelated. (Wooldridge, 2012)

The first assumption is, as discussed earlier, met. The second assumption, however, is not the case in our analyses, as we do not collect the countries randomly. We are interested in the Nordics and cannot choose other countries than Sweden, Finland, Denmark and Norway. The model also runs best without serial correlation between the idiosyncratic errors.

It is important to mention that results in a fixed effects analysis cannot be generalized. (Borenstein, Hedges, Higgins, Rothstein, 2009).

3.2 First Differences

In the first differences method, the unobserved fixed effect is eliminated by subtracting the observation for the previous time-period from the observation for the current time-period, for all time-periods (Dougherty, 2011).

Assume that we have a two-year cross-sectional model, defined by Wooldridge (2012):

4) $Y_{i,2} = (\beta_0 + \delta_0) + \ \beta_1 X_{i,2} + \alpha_i + u_{i,2}\ (t = 2)$

5) $Y_{i,1} = \beta_0 + \ \beta_1 X_{i,1} + \alpha_i + u_{i,1}\ (t = 1)$

We can then subtract the second equation from the first and get the “first differences equation”:

6) $\Delta Y_i = \delta_0 + \beta_1 \Delta X_i + \Delta u_i,$

Where our Δ, determines the change from year $t-1$ to year t. As in the fixed effects model, the unobserved fixed effect a_i, is differenced away. This is explained by the fact that a_i is time constant, giving the equation $(\alpha_i - \alpha_i) = 0$.

After differencing, our model will appear like this:

7) $\Delta Y_{i,t} = \delta_0 + \beta_1 \Delta X_{i,t,1} + \cdots + \beta_k \Delta X_{i,t,k} + \beta_D \Delta D + \Delta u_{i,t},$

where β_i is the coefficient for every independent variable.

If $u_{i,t}$ follows a random walk, meaning that there is a substantial positive serial correlation, the difference $u_{i,t}$ is serially uncorrelated and first differencing is a better model than fixed effects (Wooldridge, 2012). The first differences model can also be a better framework when the assumption of “strict exogeneity” fails, as it allows $x_{i,t}$ to be correlated with unobservable variables that are constant over time. In addition, fixed effects can be more sensitive to nonnormality and heteroscedasticity, especially when T > N.

A consequence of first differencing is that we lose our first year of measurement for each panel. Other problems might occur if the independent variables do not vary much over time, or do not vary at all (Wooldridge 2012). This can lead to serious bias in the estimation. We do, as mentioned, not see small variations within our variables and do not address this as a problem. ‘

3.3 Difference in Differences

There are several previous studies using the fixed effects framework when analyzing the determinants of venture capital activity. We do in addition use a difference in differences inspired approach when building the most appropriate empirical model for this study.

With the difference in differences analyses, the idea is to be able to measure the effect of a shock in a shock-affected country relative to a non-shock-affected country. The difference in differences approach is a version of the fixed effects model using aggregated data (Angrist and Pischke, 2008).

The model is illustrated with Denmark (dk) being a reference against Sweden (se), Finland (fi) and Norway (no). The difference in differences analyses use the difference between the venture capital activity (number of companies invested in and the amount invested) between each country and Denmark.

Let
$Y_{1,i,t} = VC\ activity\ in\ a\ shock\ affected\ country$
$Y_{o,i,t} = VC\ activity\ in\ a\ non\ shock\ affected\ country$

8) $E\left(Y_{0,i,t} \middle| i,t\right) = X_{i,t} + a_i$

Where i denotes country and t denotes time-period. The method assumes that the venture capital activity outside a shock is a result of a nation's sum of independent variables (X_t) and a time-invariant country effect (a_i). The country effect works as the unobserved individual effect.

We let $D_{i,t}$ be a dummy (=1) inside the three-year shock window.

A difference in differences analysis assumes that $E\left(Y_{1,i,t} - Y_{0,i,t} \middle| i,t\right)$ is constant and denoted as β, giving us:

9) $Y_{i,t} = X_{i,t} + \beta D_{i,t} + a_t + u_{i,t}$,

where $E\left(u_{i,t} \middle| i,t\right) = 0$. From here, we get

10) $E\left(Y_{i,t} \middle| i = dk, t = inside\right) - E\left(Y_{i,t} \middle| i = dk, t = outside\right) = X_{inside} - X_{outside}$

and

11) $E\left(Y_{i,t}\middle|i = se\ or\ fi, t = inside\right) - E\left(Y_{i,t}\middle|i = se\ or\ fi, t = outside\right)$
$$= X_{inside} - X_{outside} + \beta$$

Subtracting equation 11 from 10, we get the difference in differences equation.

12) $(X_{inside} - X_{outside}) - (X_{inside} - X_{outside} + \beta) = \beta$, the causal effect of interest.

The difference in differences method illustrated above cannot be directly transferred to our analysis. The intuition behind the model is, however, used when building the appropriate model.

3.4 The Model

As there are no previous studies that can be used as a guideline concerning the correct empirical model, it has been necessary to build a somewhat unique model for this study.

Our analyses are done with a difference in differences inspired approach in the panel data frameworks mentioned earlier (fixed effects and first differences). Denmark has not experienced any significant shock, making it appropriate to use the country as a reference. We calculate the differences in the venture capital industry and the independent variables between the shock-affected countries and the non-shock-affected country (Denmark) and use these differences in our panel data analyses. The shock is, as mentioned, implemented in the panel as a dummy variable.
The analyses implemented run the following panel regression with a fixed effects and a first differences framework:

13) $Y_{i,t} - Y_{dk,it} = \beta I_{i,t} + \beta M_{i,t} + \beta IPO_{i,t} + \beta U_{i,t} + \beta R\&D_{i,t} + \beta GDP_{i,t} + \beta D + \alpha_i + u_{i,t}$

$$for \quad i = 1,2,3\ and\ t = 1, .. ,16$$

Where:

I = $10yrgov.bond_{i,t} - 10yrgov.bond_{dk,t}$

M = $marketgrowth_{i,t} - marketgrowth_{dk,t}$

IPO = $IPOdivestments_{i,t} - IPOdivestments_{dk,t}$

U = $Adj.Unemployment_{i,t} - Adj.Unemployment_{dk,t}$

R&D = $\left(R\&D/GDP_{i,t}\right) - (R\&D/GDP_{dk,t})$

GDP = $GDP\ per\ capita\ growth_{i,t} - GDP\ per\ capita\ growth_{dk,t}$

D = $Dummy\ for\ the\ shock,$

and

(a) $Y_{i,t} - Y_{dk,t} = \left(Allventure_{i,t} - Allventure_{dk,t}\right)$

(b) $Y_{i,t} - Y_{dk,t} = \left(Seedstartup_{i,t} - Seedstartup_{dk,t}\right)$

(c) $Y_{i,t} - Y_{dk,t} = \left(Hightech_{i,t} - Hightech_{dk,t}\right)$

(d) $Y_{i,t} - Y_{dk,t} = \left((Hightech_{i,t} - Sector_{i,t}\right) - \left(Hightech_{dk,t} - Sector_{dk,t})\right)$

$i = Sweden, Finland\ and\ Norway$

$dk = Denmark$

$Sector\ =\ life\ science\ /\ business\ \&\ industrial\ products\ /\ energy\ \&\ environment$

for the different analyses conducted.

Norway has not experienced a shock, but the difference between Norway and Denmark has been included in our panel as a control measure.

The effect of the major layoffs is examined concerning the amount invested and the number of companies invested in, on three different levels; all venture (a), seed & start-up (b) and at the sector level (c and d), giving the analysis broad and detailed information. The sector analyses include an examination of the difference between the venture capital activity in the high-tech sector in country i and the high-tech sector in dk (c), as well as the differences between sectors in i , relative to identical sectors in dk(d). When investigating differences between sectors, we use the difference between high-tech and the following sectors; life science, business & industrial products and energy & environment as shown above.

We use life science as the main comparable sector, as this is the most similar to high-tech regarding R&D importance and size. The two other sectors are chosen to prevent selection bias and as robustness checks for the results.

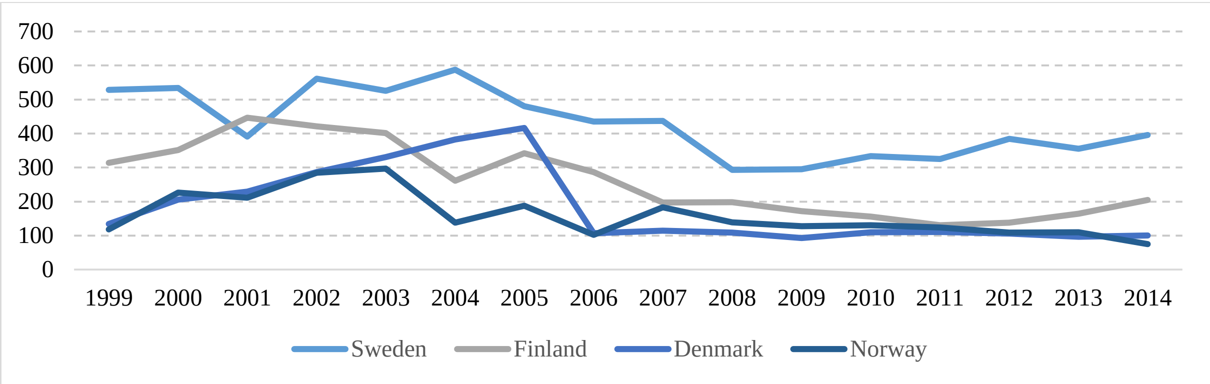
The analyses in this paper have more than two time-periods, and adjusting for time trends in the dependent variable can be done by including time-period dummies in addition to the intercepts (Wooldridge, 2012). As we see no trend in our dependent variables, this has not been included.

The different approaches enable us to measure the change in the venture capital activity from different perspectives giving the results presented higher credibility.

3.5 Pre-Regression Findings

Before presenting the results from the conducted regressions, we look at the effect of a shock at a general level. We introduce several graphs, illustrating the number of companies invested in and the amounts invested in venture capital.

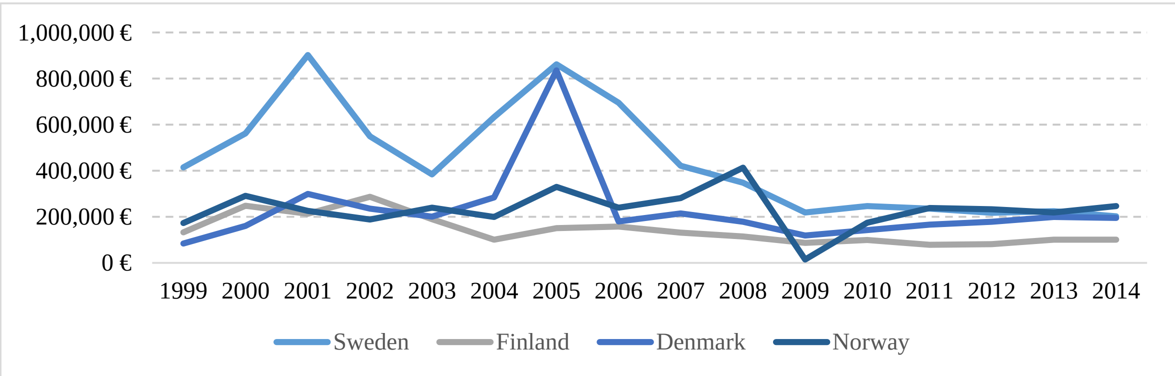
Figure 3: Number of companies invested in, all venture



Data from EVCA

Looking at figure 3, one can see that the number of companies invested in, in all venture, increased in Sweden and Finland in their respective shock windows. This can indicate that the number of companies invested in, in the shock-affected countries increased.

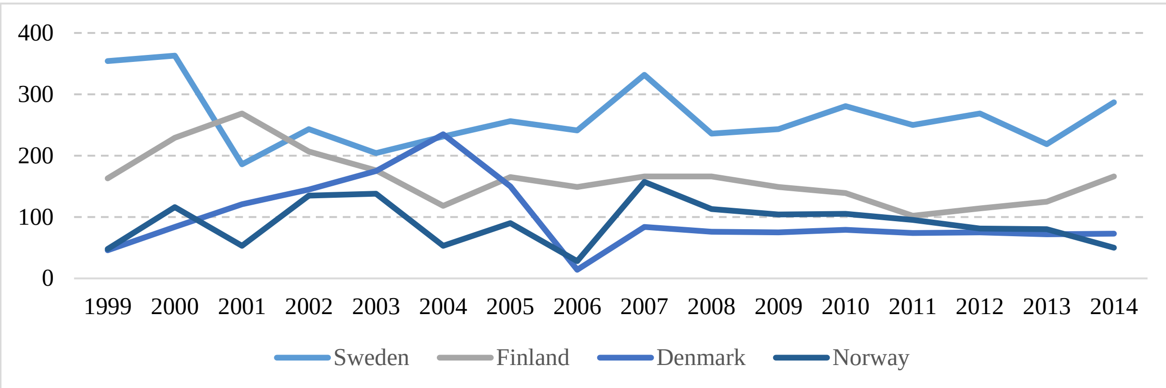
Figure 4: Amount invested, all venture (all numbers in x1000)



Data from EVCA

Figure 4 illustrates that the total amount invested in venture capital decreased in Sweden after Ericsson's shock. The decrease in Sweden is much steeper than in Denmark and Norway, and can intuitively be explained by fear among investors, which might be a consequence of the shock and the recent IT-bubble. In Finland in 2012, one can see that the invested amount increased, but there is no significant difference.

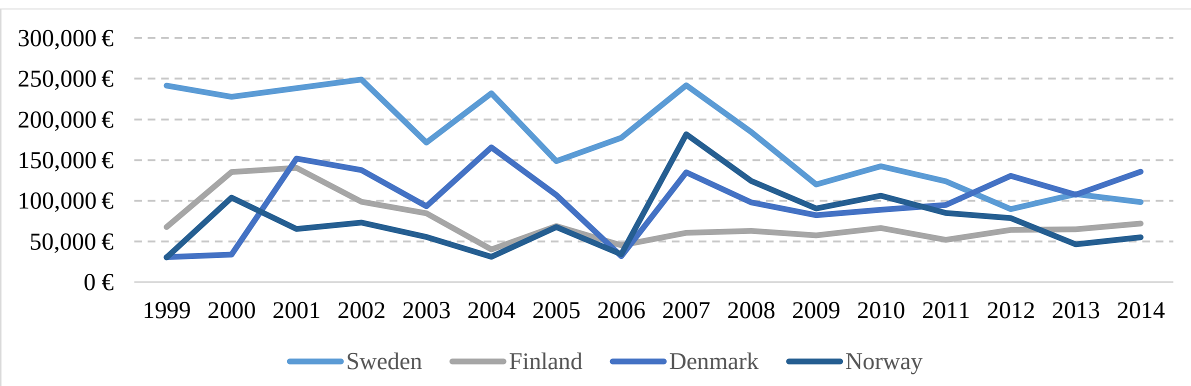
Figure 5: Number of companies invested in, seed & start-up



Data from EVCA

Figure 5 indicates an increase in the number of companies invested in, in seed & start-up, in both Sweden and Finland. Sweden's total number of companies invested in fluctuated during the shock window, while Finland seems to have had a steady increase after Nokia's shock.

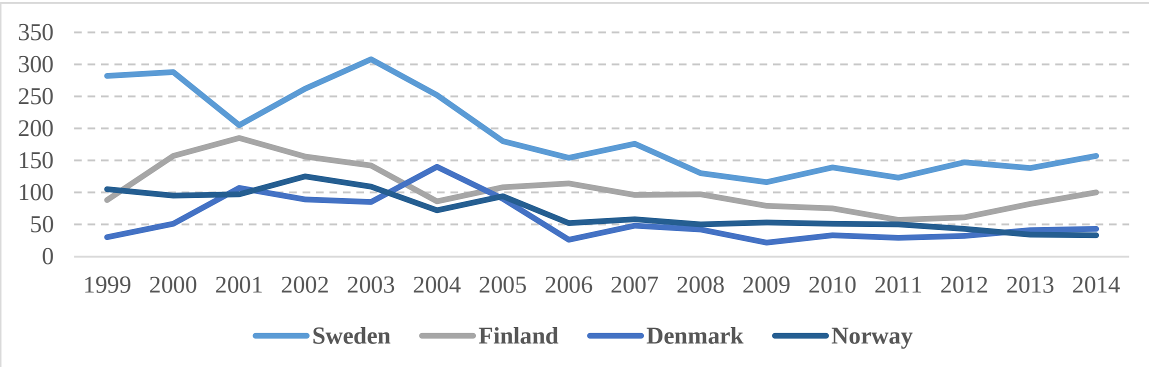
Figure 6: Amount invested, seed & start-up (all numbers in x1000)



Data from EVCA

From figure 6, we can see that the amount invested in Sweden had a small increase from 2001 to 2002, and a steep decrease from 2002 to 2003. The decrease was steeper than other Nordic countries, while Finland had a small increase after their shock. An interesting observation is that the slope for Sweden's amount invested was steeper than the decrease in the number of companies invested in. The opposite is the case in Finland, where the slope for the number of companies invested in was steeper than the increase in the amount invested. This indicates that the number of companies invested in, is positively affected relative to the amount invested.

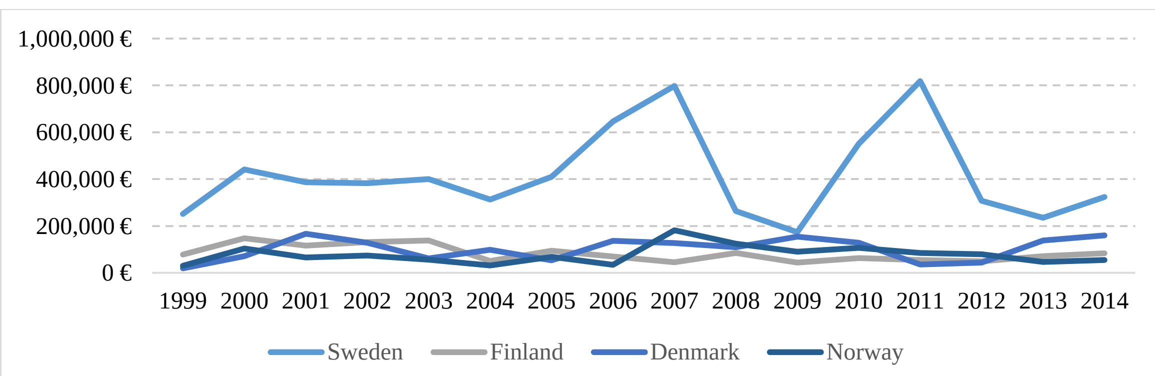
Figure 7: Number of companies invested in, high-tech



Data from EVCA

The number of companies invested in, in high-tech (figure 7) increased after a shock, which is an interesting discovery. The increase can be seen in the shock-affected countries and move opposite from the non-shock-affected countries, indicating that the hypotheses regarding the effects of a shock are correct.

Figure 8: Amount invested, high-tech (all numbers in x1000)



Data from EVCA

The total amount invested in the high-tech sector (figure 8), in Sweden, seems to have had a small increase while Finland's amount invested remained steady.

The graphs illustrate that a shock looks to affect the number of companies invested in different than the invested amount. One can see that a shock-affected industry seems to be positively affected regarding number of companies invested in, while the amount invested seems less, or even negatively affected. The graphs do not show any clear indications but might give some signals on what we can expect to find in the coming regression analyses.

3.6 Results, Difference in Differences

In this section, we present several tables showing a shock's impact on the difference in the venture capital activity between a shock-affected country and a non-shock-affected country in the Nordics. We do, as previously mentioned, measure the differences in the venture capital activity using Denmark as a reference.

The coefficients in the analyses concerning the number of companies invested in illustrate the average annual effect (positive/negative) from the shock, on the difference in each dependent variable, within the three-year window. The coefficients in the analyses regarding the amount invested show the average annual effect from a shock on the difference between the invested amounts, displayed in EUR 1000.

The shock window is as mentioned in chapter 2.6 one year after Ericsson and Nokia's biggest loss, and the same year as their largest domestic layoff. The shock window lasts three years, as we assume that the released human capital has entered an agreement with a new employer or started up his or her own business within three years.

The first differences model will be the most appropriate for this examination (discussed in chapter 4.2), suggesting that the results from this framework should be emphasized. We include two types of analyses, one with non-lagged and one with lagged independent variables, as previous studies have shown that this has a significant effect on the venture capital activity (Gompers and Lerner, 1999). The analyses are done on three different levels; all venture, seed and start-up and on sector levels.

Some coefficients differ from the fixed effects models and the first differences models, which may be explained by the difference between fixed effects demeaning and first differences first difference estimation, as well as fixed effects being more sensitive to heteroscedasticity and serial correlation.

3.6.1 Number of Companies Invested in

Table 1. Summary of the shock's effect on number of companies invested in

	Fixed Effects		First Differences	
Shock	**Model 1**	**Model 2**	**Model 3**	**Model 4**
All Venture	-20.07	0.18	62.73	87.92*
	(-0.46)	(0.00)	(1.15)	(1.90)
Seed and Start-up	-73.75**	-71.38*	-8.85	-19.93
	(-2.23)	(-1.98)	(-0.32)	(-0.54)
High-Tech	39.59**	29.31	55.04**	39.57*
	(2.17)	(1.59)	(2.11)	(1.76)

Table 1 reports a summary of the effect from a shock on the number of companies invested in, in all venture, seed & start-up and the high-tech sector. The dependent variable is determined by $(Y_{i,t} - Y_{dk,t}), i = se, fi, no.$ Where Y is the number of companies invested in, on each of the respective levels, with Denmark (dk) as a reference. The table reports results from two separate panel data approaches, fixed effects and first differences. Model 1 shows the result from a fixed effects (FE) model without lag in the independent variables while model 2 shows the results from a FE model with lag in the independent variables. Model 3 shows the results from a first differences (FD) without lag and model 4 illustrates the results from a FD model with lag. In parentheses, we present the t-statistics for each variable. The first differences estimations are run with vca (robust) command in Stata, giving us slightly different significance levels compared to fixed effects. The t-statistics are significant at the following levels: ***p<0.01, **p<0.05, *p<0.1. For the entire analyses, see appendix 7.2 (table 7, 8 & 9)

All Venture: The aggregated analysis shows that the shock has one negative and one positive coefficient in the fixed effects model, but two positive coefficients in the first differences approach. The coefficients are, however, not significant in neither model 1, 2 nor 3. In model 4, the effect of a shock is significant at the 10% level, with the coefficient being 87.92, indicating that the number of companies invested in will on average get a positive effect of 88 companies annually within the shock window.

Seed and Start-up: When studying the number of companies invested in, in seed and start-up, the results are more consistent, but contrary to our expectations. In the fixed effects framework, both model 1 and 2 show a negative and significant (5% and 10% level) coefficient for the shock. The coefficients are -71.38 and -73.75, indicating that a shock will decrease the number of companies invested in with on average 71 and 74 companies annually. When measuring the effect with the first differences approach, we see that model 3 and 4 somewhat support the findings in the fixed effects models. The coefficients are, however, not significant.

High-tech: The impact on the high-tech sector is consistent with our expectations as both model 1 and 2 show a positive coefficient. In model 1, the coefficient for the shock is 39.59, which is significant at the 5% level. As we turn to the first differences models we find that the shock had a positive and significant effect in model 3 (5% level) and in model 4 (10% level). Model 3 shows a coefficient of 55.04 and model 4 shows a coefficient of 39.57, meaning that the number of companies invested in increased on average between 40 and 55 companies annually.

Conclusion: The shock shows a positive coefficient in three models concerning all venture. The coefficient is, in addition, significant at the 5% level in model 4, which somewhat supports our hypothesis that a shock will cause an increase in the number of companies invested in. Model 4 indicates that the companies invested in will increase on average by 88 annually, within the 3-year shock window. The coefficient in model 1 does appear negative and insignificant, making it difficult to conclude on the effect. We emphasize the first differences models, which suggest that the shock has a positive effect on the activity.

Concerning the number of companies invested in, in seed & start-up, the results are unambiguous. Model 1 and 2 are negative and significant at the 5% and 10% level while model 3 and 4 are negative and insignificant. The results give us a reasonable reason to assume that a shock will affect the number of companies invested in, in seed and start-up negatively. The average number of companies invested in will decrease by between 71 and 74 companies compared to a non-shock affected country.

The number of companies invested in, in the shock-affected sector has positive and significant coefficients in three models. They are significant at the 5% and 10% level, which implies that a shock has a positive effect on the number of companies invested in. The results suggest that the difference in the number of companies invested in on average increase between 40 and 55 annually.

3.6.2 Amount Invested

The analyses concerning the amount invested are conducted similarly to the above, including all-venture, seed & start-up and the high-tech sector.

Table 2. Summary of the shock's effect on amount invested

	Fixed Effects		First Differences	
Shock	**Model 1**	**Model 2**	**Model 3**	**Model 4**
All Venture	79278.93	83402.39	-62127.34	90630.83
	(0.88)	(1.03)	(-0.57)	(0.81)
Seed and Start-up	29365.19	25381	30376.08	22173.48*
	(1.14)	(0.93)	(1.18)	(1.96)
High-Tech	-45638.35	-17679.77	-49477.33	34006.82
	(-0.76)	(-0.25)	(-0.56)	(0.32)

Table 2 reports a summary of the effect from a shock on the amount invested in all venture, seed & start-up and the high-tech sector. The dependent variable is determined by $(Y_{i,t} - Y_{dk,t})$, $\mathrm{i} = se, fi, no$. Where Y is the amount invested on each of the respective levels, with Denmark (dk) being a reference. The table reports results from two separate panel data approaches, fixed effects and first differences. Model 1 shows the result from a fixed effects (FE) model without lag in the independent variables while model 2 shows the results from a FE model with lag in the independent variables. Model 3 shows the results from a first differences (FD) without lag and model 4 illustrates the results from a FD model with lag. In parentheses, we present the t-statistics for each variable. First differences estimation is run with vca (robust) command in Stata, giving us slightly different significance levels compared to fixed effects. The t-statistics are significant at the following levels: ***p<0.01, **p<0.05, *p<0.1. For the entire analyses, see appendix 7.2 (table 10, 11 & 12)

All Venture: The fixed effects approach shows that the invested amount in all venture capital has a positive coefficient for the shock. The coefficients are, however, not significant in neither of the analyses. When measuring the effect with first differences it appears that the shock has a negative and insignificant coefficient in model 3, but a positive and insignificant coefficient in model 4. The insignificant coefficients are in line with our expectations that there is little correlation between a shock and the invested amount.

Seed and Start-up. Models 1 and 2 show a positive coefficient for the invested amount in seed and start-up, but none appears significant. The first differences supports the findings, as model 3 and 4 both show positive coefficients. Model 4 is, in addition, significant at the 10 % level, which implies that a shock leads to a higher amount invested. The coefficient is 22173.48, indicating that the difference in the amount invested will increase on average with €22,173,480 annually in respect of a non-shock-affected country.

High-Tech: Our results suggest negative coefficients for the shock in three models. The two fixed effects models show a negative coefficient while model 3 is the only first differences model showing the same. Model 4 shows a positive and insignificant coefficient for the shock. None of the analyses has significant coefficients, which indicate that a shock did not affect the invested amount in high-tech.

Conclusion: The shock does not show any significant effect on the invested amount in all venture capital. When measuring the effect on the invested amount in seed and start-up we see that there is a broad unity between the models, which indicates that the shock has a positive effect. The shock has, in addition, a significant effect at the 10% level in model 4. The model suggests that the average difference in the invested amount will increase by €22,173,480 in respect of a non-shock-affected country. This is interesting, as the amount invested seems to increase, while the number of companies seems to decrease. When examining a shock's impact on the amount invested in the shock-affected sector, we see that there are no significant coefficients, indicating that the invested amount does not significantly differ from zero. This gives reason to believe that the invested amount in a sector experiencing a major layoff will not be influenced. The findings are contrary to the number of companies invested in, where we could conclude that a shock has a positive effect on the shock-affected industry.

3.7 Results, the Differences between Sectors

The previous analyses investigate the effect of a shock on three different levels. They show that there is an increase in the number of companies invested in, in the shock-affected sector, relative to the same sector in Denmark. In addition, they indicate little to no significant effect on the amount invested. To measure if this result is consistent and robust, we examine the difference between the high-tech sector and several other sectors in the shock-affected countries, relative to the same sectors in Denmark.

Life science is chosen as the main control sector as it is the most similar in regards to size and other characteristics such as R&D/human capital importance. We also include the business & industrial products and the energy & environment sectors as robustness checks.

3.7.1 Number of Companies Invested in

Table 3. The difference between high-tech and three different sectors, number of companies invested in

	Fixed Effects		First Differences	
Shock	**Model 1**	**Model 2**	**Model 3**	**Model 4**
High-Tech vs. Life-Science	60.63***	-3.42	74.00**	31.97*
	(2.79)	(-0.14)	(2.11)	(1.90)
High-Tech vs. Business & Industrial Produts	35.06*	21.70	50.31**	29.14
	(1.99)	(1.19)	(2.63)	(1.62)
High-Tech vs. Energy & Environment	51.67***	39.40**	53.25*	33.90
	(2.86)	(2.17)	(1.93)	(1.14)

Table 3 reports a summary of the effect from a shock on the difference in the number of companies invested in, between high-tech and the three sectors: life science, business & industrial products and energy & environment. The dependent variable is determined by $(Y_{i,t} - Y_{dk,t}), i = se, fi, no$. Where Y is the difference between the high-tech sector and the three other sectors respectively, with Denmark (dk) as a reference. The table reports results from two separate panel data approaches, fixed effects and first differences. Model 1 shows the result from a fixed effects (FE) model without lag in the independent variables while model 2 shows the results from a FE model with lag in the independent variables. Model 3 shows the results from a first differences (FD) without lag and model 4 illustrates the results from a FD model with lag. In parentheses, we present the t-statistics for each variable. First differences estimation is run with vca (robust) command in Stata, giving us slightly different significance levels compared to fixed effects. The t-statistics are significant at the following levels: ***p<0.01, **p<0.05, *p<0.1. For the entire analyses, see appendix 7.3 (table 13, 14 & 15)

High-tech vs life science. Testing the shock's effect on the difference between high-tech and life science supports our previous findings. The fixed effects approach gives a positive and significant (1% level) coefficient in model 1, but a barely negative one in model 2 (non-significant). In the first differences analyses, the increase appears significant in both model 3 and 4 (5% and 10% level) suggesting an average annual positive effect (increase) in the number of companies invested in between 32 and 74 within the shock-window. With positive and significant coefficients in three out of four models, the results indicate that the number of companies invested in increased relative to life science.

High-tech vs business & industrial products (BIP). The results are consistent with the comparison with life science. The results from the fixed effects models indicate positive coefficients, with model 1 being significant at the 10% level. The first differences models also indicate positive coefficients, with model 3 suggesting significance at the 5% level. All coefficients are positive, indicating a positive increase in the difference between high-tech and BIP by an average of 35 and 50 annually.

High-tech vs energy & environment (E&E). The comparison between these sectors also indicates a positive and significant coefficient for the shock. The two fixed effects models suggest a positive and significant effect at the 1% and 5% level respectively. The first differences models support this with positive coefficients. Model 3 is, in addition, significant at the 10% level. The results indicate an average annual increase in the difference between high-tech and the energy & environment sector of between 39 and 53, which is consistent with both previous sector analyses.

Conclusion*:* The shock shows positive and significant coefficients in eight out of twelve analyses. In addition, all but one of the insignificant analyses have a positive coefficient for the shock. We emphasize the first differences model, but the results are highly supported by the fixed effects estimations. An interesting result is that the non-lagged models (1 and 3), get a positive and significant coefficient compared to all sectors. The significant coefficients suggest an average annual increase in the difference between the shock-affected sector and non-shock affected sectors of between 32 and 74 companies invested in, which is consistent with our hypothesis and supports the results in chapter 3.6.1.

3.7.2 Amount Invested

As in previous analyses, we include the differences in the invested amount and measure the effect on high-tech relative to three other sectors.

Table 4 The difference between high-tech and three different sectors, amount invested

	Fixed Effects		First Differences	
Shock	**Model 1**	**Model 2**	**Model 3**	**Model 4**
High-Tech vs. Life-Science	-196796.9	-161419.4	106275.3	-141142.8
	(-1.14)	(-1.00)	(0.45)	(-0.99)
High-Tech vs. Business & Industrial Produts	20091.89	15167.29	223442.8	244675.2*
	(0.17)	(0.11)	(1.57)	(1.69)
High-Tech vs. Energy & Environment	42081.2	55472.6	-88627.27	-16786.68
	(0.51)	(0.62)	(-0.78)	(-0.14)

Table 4 reports a summary of the effect from a shock on the difference in the amount invested between high-tech and the three sectors: life science, business & industrial products and energy & environment. The dependent variable is determined by $(Y_{i,t} - Y_{dk,t}), i = se, fi, no$. Where Y is the difference between the high-tech sector and the three other sectors respectively with Denmark (dk) as a reference. The table reports results from two separate panel data approaches, fixed effects and first differences. Model 1 shows the result from a fixed effects (FE) model without lag in the independent variables while model 2 shows the results from a FE model with lag in the independent variables. Model 3 shows the results from a first differences (FD) without lag and model 4 illustrates the results from a FD model with lag. In parentheses, we present the t-statistics for each variable. First differences estimation is run with vca (robust) command in Stata, giving us slightly different significance levels compared to fixed effects. The t-statistics are significant at the following levels: ***p<0.01, **p<0.05, *p<0.1. For the entire analyses, see appendix 7.3 (table 16, 17 & 18)

High-tech vs life science. The shock has a negative coefficient in three of our models, indicating that there might be pessimistic views on the sector experiencing a shock. However, the result on the invested amount between the two sectors supports our findings in chapter 3.6.2, with negative, but no significant coefficients.

High-tech vs business & industrial products (BIP). All models appear with a positive coefficient, with model 4 being the only significant one (10% level). This indicates a positive effect from the shock and suggests that there was a larger decrease in the amount invested in BIP than in high-tech. The fixed effects support the first differences, but none of the models show significance. The result is contrary to other sectors, which show no significance at all.

High-tech vs energy & environment (E&E). The analyses show, similar to the previous ones, no significant coefficients, but the fixed effects and first differences approach indicate contrary coefficients. The fixed effects models show positive coefficients while the first differences models show negative coefficients. As mentioned, the coefficients do not significantly differ from zero, which suggests that the shock did not have any effect on the difference between the sectors.

Conclusion*:* Eleven out of twelve analyses show insignificant coefficients indicating that the difference in the invested amount between sectors is not affected by a shock. These results are both logical and expected. However, one analysis appears positive and significant, suggesting that the difference might be positively affected. This result is a clear minority and we therefore conclude that the amount is not affected.

3.8 Summary of Empirical Results

Aggregated results. We emphasize the first differences model when concluding with the effect of a company-related shock. We can from the results presented, have a reasonable basis to say that a shock might have a positive effect on the total number of companies invested in, in all venture. Model 4 shows a significant coefficient at the 10% level, but the fixed effects models do not support the result. The effect of the shock is insignificant in model 1, 2 and 3, which suggest that it will be difficult to say if a shock has positive effect or not. However, by emphasizing the first differences model it seems to increase.

By digging deeper, we find that a shock has negative and significant impact on the number of companies invested in, in seed and start-up. The fixed effects approach show that the coefficients are significant at the 5% and 10% level. This is partly supported by the first differences models, as they show negative but insignificant coefficients. We find it reasonable to conclude that the number of companies invested in, in seed and start-up, is negatively affected by major layoffs. This is somewhat contrary to our hypotheses, as we assumed that the number of start-ups increases with higher human capital availability.

When we look at the number of companies invested in, in the shock-affected sector separately, the results are consistent with our expectations. Model 1, 3 and 4 show significant (5% and 10% level) and positive impact from the shock while model 2 shows positive but non-significant effect. Model

2 is to some extent supporting the other models. The analyses show that a shock will have a positive effect on the number of companies invested in, in the shock-affected sector.

A very interesting result is that the amount invested in all venture capital seems to be unaffected by a shock. The amount invested in seed and start-up does however show one model with a positive and significant coefficient (model 4), which can imply that the amount invested increase. It is, however, only one model suggesting a significant effect. In addition, the amount invested in the shock-affected sector see no significant effect in line with our expectations.

Sector results. The most interesting conclusion for this thesis is, however, how the shock-affected sector reacts compared to other sectors. We can see that there was an increase in the number of companies invested in, in high-tech relative to life science with model 1, 3 and 4 showing significance at the 1%, 5% and 10% respectively.

To check if this result is robust, we run additional analyses between the high-tech sector and two other sectors. The analysis between the high-tech and business & industrial products sector supports the findings from the life science analysis. In model 1 and 3, we see that the shock had a positive and significant effect (10% and 5% level) while model 2 and 4 suggest that the shock had a positive, but non-significant effect.

In the last sector analysis, we investigate the high-tech sector compared to the energy & environment sector. It appears that the shock had a positive and significant effect in three out of four models (1%, 5% and 10% level), with the last model suggesting a positive, but insignificant effect.

The analyses indicate that the number of companies invested in, in the shock-affected sector gets a positive reaction to a shock, compared to other sectors. The sector analyses show in addition that there is no significant evidence that the amount invested in a shock affected sector increase relative to others.

4. Robustness Issues

4.1 Data

The dataset used in the analyses gives us detailed information regarding the number of companies invested in, and the total amount invested. A consequence of doing sector analyses is that the data from EVCA does not distinguish between venture capital and buyouts. This will intuitively be a major drawback when measuring the effect on sector levels. One should however remember that buyouts are driven by private equity companies' willingness to invest, and not necessarily on the number of companies available to invest in. Our findings show that the shock does not affect the invested amount, indicating that buyouts will not be affected by a shock. The lack of data on sector levels is not optimal, but our findings in the analyses regarding the invested amount suggest that this does not have a major impact for our results.

Our panel consists of four countries with 64 observations, but by using Denmark as a reference, we lose 16 observations. A result of excluding Denmark is that our analyses are run with 45 (first differences) and 48 (fixed effects) observations. This is not ideal, as one should preferably have a higher number of observations.

4.2 Empirical Framework

Several measurements and tests are implemented to ensure that the correct empirical framework is used, which makes sure that the presented results in this report are trustworthy and robust.

As mentioned earlier in the report, a pooled OLS model assumes homoscedasticity, normality and no serial correlation between the independent variables and the composite error. To check if our dataset has homoscedasticity we use a modified Wald test for group-wise heteroscedasticity. The null hypothesis is that $\sigma_i^2 = \sigma^2$ i.e. that the variance is the same, making it homoscedastic. We can reject the null-hypothesis in some of the conducted analyses, indicating that we have a mix of heteroscedasticity and homoscedasticity. The modified Wald test has proven to be very poor in panels with large N and small t (Baum, C.F, 2008). This is however not the case in our dataset, making the modified Wald test appropriate. The test can also be used when the dataset is not normally distributed.

To check for normality we use a modified Jarque-Bera test, which uses a bootstrapping method to take account for missing observations. The test uses both the skewness and the kurtosis and combines them into a joint p-value. The null-hypothesis in the test is simply that there is normality (Brooks, 2014). The test can similar to the above be rejected in some analyses and not rejected in others. There have been critics against such tests and because of the fact that we have a rather small dataset, we are not able to conclude if there is normality or not.

Another factor that can cause bias in the results is the presence of serial correlation between the idiosyncratic errors. To check for serial correlation in our dataset, a Wooldridge test is used (Drukker, D.M, 2003). The test indicates that there is a presence of autocorrelation in our dataset.

Heteroscedasticity can be managed with a vce robust measure, and we cannot conclude whether the data has normality. The fact that there is a presence of autocorrelation point in the direction of a method other than pooled OLS. The most important argument against pooled OLS is, however, the fact that we want to treat each country individually and not in a pool.

We have for safety reasons conducted the Breusch-Pagan Lagrangian multiplier test to check whether we should use a pooled OLS or a random effects estimation. The null-hypothesis for the Breusch-Pagan test is that the variance for the unobserved term is zero. We cannot reject the null-hypothesis, indicating that there is no significant difference across countries and that country-specific effects are not random (Baltagi, Badi; Feng, Qu; and Kao, Chihwa, 2012). This indicates that a pooled OLS will be more appropriate.

The F-test in the fixed effects estimation is used when determining whether we should use a pooled OLS method or a fixed effects model. This test the significance of the fixed effects intercepts. The H0 in the test is that the intercepts from the fixed effects are zero (Wooldridge, 2002). The null-hypothesis is rejected which implies that a fixed effects model will be the most appropriate framework for this study.

Our independent variables are time variant, meaning that they vary over time, which is necessary if a fixed effects model is to be used. We also assume that the individual specific effects have a correlation with our independent variables. The fixed effects estimator seems to be appropriate, but we use the Hausman's specification test to see if this is the case. The H0 is that the difference in coefficients is not systematic. The random effects model should be used if the H0 is not rejected (Wooldridge, 2012). The Hausman test for our analysis is significant at the 1% level, indicating that we can reject the null-hypothesis.

From the different implemented tests, we know that the pooled OLS and the random effects model will give biased results. In addition, pooled OLS will ignore time-invariant country-specific effects and the random effects model does not assume correlation between each country's specific effect and the independent variables. Thus indicating that a fixed effects model will be most appropriate. The fixed effects model has in addition been used in several previous studies, which supports our choice.

The question is then if we should use a fixed effects model or a first differences estimation. If our dataset only consisted of two time-periods, the two will be the same. However, if the time-period is three or more, there will be a difference between them (Wooldridge, 2012). We know that the estimation techniques assume strict exogeneity, a random sample in the cross sections and variance in variables across time, making both models usable. A way to measure the two estimation techniques will be their relative efficiencies. The efficiency of the techniques depends on whether the dataset has serial correlation or not. If the idiosyncratic error is serially uncorrelated a fixed effects estimation will give answers that are more precise. However, with serially correlated idiosyncratic errors, a first differences estimation is better (Drukker, D.M, 2003). The Wooldridge test indicates a clear auto-correlation, which is in favor of a first differences model. In addition, we know from discussions in chapter 3.2 that first differences will be better if the assumption about strict exogeneity is violated and especially when T > N.

It is nevertheless very difficult to conclude which of the two models that are best suited for our analyses, which is why we include both the fixed and the first differences estimation. By doing so, the results in the report should be robust and trustworthy.

A problem that should be mentioned is that by including the vce robust in our fixed effects estimation, we get a massive reduction in the degrees of freedom (because of clustering). By running the command, the answers appear dubious. From a correspondence with a highly respected econometrics professor at NYU Stern, who stated that the problem was not perfectly defined in theory and that this might be a flaw in STATA, we decided to run the fixed effects estimations without the command. The first differences model does not get this massive reduction in the degrees of freedom, which is why we run these with vce robust.

5. Conclusion

In this paper, we present several empirical analyses in different panel data frameworks on the effect of company-related shocks i.e. major layoffs on the venture capital activity. Our conclusions are based on a comparison between several models with fixed effects and first differences estimations, making the conclusion robust. The analyses are done with several different perspectives and show that a shock does not have a direct impact on the differences between the invested amounts. The analyses do, however, show that the average difference in the number of companies invested in, in the shock-affected sector/country increase, with respect to non-shock affected sectors/countries.

Our analyses indicate that the number of companies invested in, in venture capital has a positive effect of, on average, 90 companies annually following a shock. The analyses also indicate that the average number of companies invested in, in seed and start-up will be negatively affected. Our models suggest that the number of companies will decrease, on average, between 71 and 74 companies annually. This is an interesting result, as one should assume that the start-up activity would increase after a major layoff.

We see, however, that the shock-affected sector, will be positively affected as our results suggest an average effect of between 40 and 55 companies invested in annually, relative to the same sector in Denmark. This is interesting, as the total number of companies invested in decrease in seed and start-up. Indicating that venture capital shifts focus to the shock-affected sector, even though the total companies invested in, in seed and start-up decrease.

The results from the analyses between sectors imply the same as the above, giving credibility to the results. The analysis between high-tech and life science suggests that the shock had, on average, a positive effect of 32-74 companies invested in annually. The same analysis between high-tech and business & industrial products indicates a positive effect of 35-50 companies while the analysis between high-tech and the energy & environment sector indicates a positive effect of 39-

53 companies. All analyses indicate that the number of companies invested in, in a shock-affected sector is positively affected relative to non-shock-affected sectors.

The results show that the released human capital (from layoffs) tends to return to the same sector. The proposed appropriations from the Norwegian government will therefore have a positive effect now, as the country is experiencing an increase in available human capital.

We do not claim that the amount of capital is not important, but rather that a sudden increase in available human capital has a significant effect on the number of companies invested in, in a shock-affected sector/country. The increase will most likely be a result of higher start-up activity. We suggest that professionals follow up on the research, and remind the reader that the above conclusion cannot be generalized.

6. Future Research

As this is the first academic research done on company-related shocks and the venture capital activity, we highly encourage that the problem will be further researched in the future. We suggest that future researchers investigate if there is a connection, not only in sectors but also in more specific geographical locations. We intended to investigate if there is a connection with company-related shocks and cities/postal codes, but this was not doable due to a lack of data. This is however very interesting, and should be investigated in the future.

7. Appendices

7.1 Tables

7.1.1 Data Summary

Table 5. Data Summary

Variables	Obs	Mean	Std. Dev	Min	Max
Country	48	2	1	1	3
t	48	9	5	1	16
Yield - gov.bond	48	0%	1%	-1%	2%
Market growth	48	-4%	17%	-75%	36%
IPO divestments	48	7	9	-5	43
Adjusted unemployment	48	1%	3%	-4%	6%
R&D expenditures in % of GDP	48	0%	1%	-3%	3%
GDP per capita growth	48	1%	5%	-8%	13%
Shock	48	0	0	0	1

Table 5 reports a summary of included independent variables. The table reports the number of observations, the mean, standard deviation, the minimum and the maximum value in the observation period. The observation period is between 1999 and 2014, and includes Sweden, Finland, Norway and Denmark. Gov.Bond is the yield on a 10-year government bond in the specific country. Market growth is the annual average return on the countries' market indices. Unemployment is the average annual unemployment rate in each country. R&D expenditures is the annual R&D expenditures in the country in percentage of GDP and GDP capita growth is the annual growth of GDP per capita. The shock is a dummy variable.

7.1.2 Correlations

Table 6. Correlations

Variables	Yield - gov.bond	Market growth	IPO divestments	Unemployment	R&D expenditures	GDP per capita growth	Shock
Yield - gov.bond	1						
Market growth	-0.1818	1					
IPO divestments	-0.3296	-0.1504	1				
Unemployment	-0.5306	-0.0005	0.1534	1			
R&D expenditures	-0.4536	0.0915	0.2994	0.7088	1		
GDP per capita growth	0.2139	0.0925	-0.019	-0.225	-0.1536	1	
Shock	0.0849	-0.1705	-0.0652	-0.0038	0.0608	-0.1157	1

Table 6 reports a correlation matrix of the independent variables. We have included several independent variables that have shown to have an impact on our dependent variables. If the variables are highly correlated, they may bias the result in the regressions. To be sure that the results in our regressions are not bias, a correlation analysis is conducted. If independent variables are highly correlated, one of them should be considered excluded from the model. The table indicates that none of our independent variables are highly correlated, giving us no reason to exclude any variables. Gov.Bond is the yield on a 10-year government bond in the specific country. Market growth is the annual average return on the countries' market indices. Unemployment is the average annual unemployment rate in each country. R&D expenditures is the annual R&D expenditures in the country in percentage of GDP and GDP capita growth is the annual growth of GDP per capita. The shock is a dummy variable.

7.2 Tables, DD

Table 7. Number of companies invested in, all venture

	Fixed Effects		First Differences	
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Yield - gov.bond	-1364.23	-1622.46	-1285.06	856.99
	(-0.48)	(-0.58)	(-0.75)	(0.47)
Market growth	-147.45	-179.38**	-22.39	-80.85
	(-1.30)	(-2.19)	(-0.24)	(-1.61)
IPO divestments	1.29	0.61	-0.99	0.95
	(0.60)	(0.31)	(-0.23)	(0.52)
Adjusted unemployment	478.50	1083.73	2507.24*	5022.25**
	(0.39)	(1.07)	(1.75)	(2.13)
R&D expenditures in % of GDP	-1872.32	253.51	-1630.87*	1628.16*
	(-0.92)	(0.14)	(-2.01)	(1.93)
GDP per capita growth	149.87	328.80	193.66	111.60
	(0.54)	(1.23)	(0.86)	(0.65)
Shock	**-20.07**	**0.18**	**62.73**	**87.92***
	(-0.46)	**(0.00)**	**(1.15)**	**(1.90)**
Constant	93.53***	81.18***	-2.81	6.33
	(3.43)	(3.16)	(-0.18)	(0.40)
Observations	48	48	45	45
R-sq	0.1371	0.3969	0.1396	0.2801

Table 7 reports the effect of a shock on the difference in number of companies invested in, in all venture capital, with Denmark (dk) being a reference. The dependent variable is determined as $(Y_{i,t} - Y_{dk,t}), i = se, fi, no$ where Y is the in number of companies invested in venture capital. Data is collected from EVCA. The table reports results from two separate panel data approaches, fixed effects and first differences. Model 1 shows the result from a fixed effects (FE) model without lag in the independent variables, while model 2 shows the results from a FE model with lag in the independent variables. Model 3 shows the results from a first differences (FD) without lag and model 4 illustrates the results from a FD model with lag. Yield-gov.bond is the yield on a 10-year government bond in the specific country. Market growth is the annual average return on the countries' market indices. Adjusted unemployment is the average annual unemployment rate in each country. R&D expenditure is the annual R&D expenditure in the country in percentage of GDP and GDP per capita growth is the annual growth of GDP per capita. All independent variables are determined as $(X_{i,t} - X_{dk,t}), i = se, fi, no$. In parentheses, we present the values of the t-statistics for each variable. First differences estimation is run with vca (robust) command in Stata, giving us slightly different significance levels compared to fixed effects. The t-statistics are significant at the following levels: ***p<0.01, **p<0.05, *p<0.1.

Table 8. Number of companies invested in, seed and start-up

	Fixed Effects		First Differences	
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Yield - gov.bond	-756.33	-2206.90	577.30	40.24
	(-0.36)	(-0.95)	(0.46)	(0.03)
Market growth	-81.84	-93.81	-27.40	-8.95
	(-0.97)	(-1.37)	(-0.40)	(-0.14)
IPO divestments	2.59	0.12	3.21	-0.15
	(1.61)	(0.08)	(1.07)	(-0.14)
Adjusted unemployment	-212.84	119.57	2850.42**	2842.96*
	(-0.23)	(0.14)	(2.43)	(1.87)
R&D expenditures in % of GDP	-1545.26	41.50	-1705.49***	1324.63
	(-1.02)	(0.03)	(-3.09)	(1.49)
GDP per capita growth	220.47	117.99	265.20	-22.75
	(1.06)	(0.53)	(1.65)	(-0.18)
Shock	**-73.75****	**-71.38***	**-8.85**	**-19.93**
	(-2.23)	**(-1.98)**	**(-0.32)**	**(-0.54)**
Constant	67.83***	83.72***	2.85	3.12
	(3.32)	(3.91)	(0.28)	(0.26)
Observations	48	48	45	45
R-sq	0.0618	0.166	0.2871	0.1298

Table 8 reports the effect of a shock on the difference in number of companies invested in, in seed and start-up, with Denmark (dk) being a reference. The dependent variable is determined as $(Y_{i,t} - Y_{dk,t}), i = se, fi, no$ where Y is the in number of companies invested in seed and start-up. Data is collected from EVCA. The table reports results from two separate panel data approaches, fixed effects and first differences. Model 1 shows the result from a fixed effects (FE) model without lag in the independent variables, while model 2 shows the results from a FE model with lag in the independent variables. Model 3 shows the results from a first differences (FD) without lag and model 4 illustrates the results from a FD model with lag. Yield-gov.bond is the yield on a 10-year government bond in the specific country. Market growth is the annual average return on the countries' market indices. Adjusted unemployment is the average annual unemployment rate in each country. R&D expenditure is the annual R&D expenditure in the country in percentage of GDP and GDP per capita growth is the annual growth of GDP per capita. All independent variables are determined as $(X_{i,t} - X_{dk,t}), i = se, fi, no$. In parentheses, we present the values of the t-statistics for each variable. First differences estimation is run with vca (robust) command in Stata, giving us slightly different significance levels compared to fixed effects. The t-statistics are significant at the following levels: ***p<0.01, **p<0.05, *p<0.1.

Table 9. Number of companies invested in, high-tech

	Fixed Effects		First Differences	
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Yield - gov.bond	-341.34	-354.57	75.37	268.45
	(-0.29)	(-0.30)	(0.10)	(0.26)
Market growth	-18.06	-82.72**	39.06	-2.51
	(-0.39)	(2.36)	(0.90)	(-0.06)
IPO divestments	2.92***	1.48*	2.10	0.17
	(3.28)	(1.77)	(1.35)	(0.25)
Adjusted unemployment	84.19	998.29**	649.60	468.21
	(0.16)	(2.30)	(0.72)	(0.52)
R&D expenditures in % of GDP	22.42	-1642.08**	140.19	-846.23
	(0.03)	(-2.17)	(0.27)	(-1.16)
GDP per capita growth	115.43	14.57	141.44	-51.54
	(1.01)	(0.13)	(1.46)	(-0.69)
Shock	**39.59****	**29.31**	**55.04****	**39.57***
	(2.17)	**(1.59)**	**(2.11)**	**(1.76)**
Constant	40.93***	41.46***	-2.10	-4.53
	(3.63)	(3.78)	(-0.29)	(-0.67)
Observations	48	48	45	45
R-sq	0.5703	0.5342	0.1837	0.0994

Table 9 reports the effect of a shock on the difference in number of companies invested in, in high-tech, with Denmark (dk) being a reference. The dependent variable is determined as $(Y_{i,t} - Y_{dk,t}), i = se, fi, no$ where Y is the in number of companies invested in the high-tech sector. Data is collected from EVCA. The table reports results from two separate panel data approaches, fixed effects and first differences. Model 1 shows the result from a fixed effects (FE) model without lag in the independent variables, while model 2 shows the results from a FE model with lag in the independent variables. Model 3 shows the results from a first differences (FD) without lag and model 4 illustrates the results from a FD model with lag. Yield-gov.bond is the yield on a 10-year government bond in the specific country. Market growth is the annual average return on the countries' market indices. Adjusted unemployment is the average annual unemployment rate in each country. R&D expenditure is the annual R&D expenditure in the country in percentage of GDP and GDP per capita growth is the annual growth of GDP per capita. All independent variables are determined as $(X_{i,t} - X_{dk,t}), i = se, fi, no$. In parentheses, we present the values of the t-statistics for each variable. First differences estimation is run with vca (robust) command in Stata, giving us slightly different significance levels compared to fixed effects. The t-statistics are significant at the following levels: ***p<0.01, **p<0.05, *p<0.1.

Table 10. Invested amount, all venture

	Fixed Effects		First Differences	
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Yield - gov.bond	-1544327	-3173136	-1235407	-4173644
	(-0.27)	(-0.60)	(-0.38)	(-1.14)
Market growth	41605.93	-136814.8	192900	-59457.93
	(0.18)	(-0.89)	(1.32)	(-0.40)
IPO divestments	3592.65	11291.22***	-11982.62*	9799.86**
	(0.82)	(3.06)	(-1.91)	(2.70)
Adjusted unemployment	-2125522	1515641	-2587592	5545668
	(0.84)	(0.79)	(-0.73)	(1.21)
R&D expenditures in % of GDP	4731407	-4488988	5342912	-3931431
	(1.15)	(-1.35)	(1.78)	(-1.34)
GDP per capita growth	-365944.5	174633.2	82334.17	254609.9
	(-0.65)	(0.35)	(0.18)	(0.58)
Shock	**79278.93**	**83402.39**	**-62127.34**	**90630.83**
	(0.88)	**(1.03)**	**(-0.57)**	**(0.81)**
Constant	34392.26	-50458	-20370.89	1053.25
	(0.62)	(-104)	(-0.54)	(0.03)
Observations	48	48	45	45
R-sq	0.1922	0.4595	0.1886	0.2077

Table 10 reports the effect of a shock on amount invested in all venture capital, with Denmark (dk) being a reference. The dependent variable is determined as $(Y_{i,t} - Y_{dk,t}), i = se, fi, no$ where Y is the amount invested in venture capital. Data is collected from EVCA. The table reports results from two separate panel data approaches, fixed effects and first differences. Model 1 shows the result from a fixed effects (FE) model without lag in the independent variables, while model 2 shows the results from a FE model with lag in the independent variables. Model 3 shows the results from a first differences (FD) without lag and model 4 illustrates the results from a FD model with lag. Yield-gov.bond is the yield on a 10-year government bond in the specific country. Market growth is the annual average return on the countries' market indices. Adjusted unemployment is the average annual unemployment rate in each country. R&D expenditure is the annual R&D expenditure in the country in percentage of GDP and GDP per capita growth is the annual growth of GDP per capita. All independent variables are determined as $(X_{i,t} - X_{dk,t}), i = se, fi, no$. In parentheses, we present the values of the t-statistics for each variable. First differences estimation is run with vca (robust) command in Stata, giving us slightly different significance levels compared to fixed effects. The t-statistics are significant at the following levels: ***p<0.01, **p<0.05, *p<0.1

Table 11. Invested amount seed and start-up

	Fixed Effects		First Differences	
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Yield - gov.bond	-1938487	-3096878*	134648	-2146381
	(-1.17)	(-1.74)	(0.12)	(-1.61)
Market growth	13208.32	-60273.6	35674.33	28505.76
	(0.20)	(-1.16)	(0.73)	(0.70)
IPO divestments	3436.99***	1685.92	1331.69	-698.67
	(2.74)	(1.35)	(0.70)	(-0.57)
Adjusted unemployment	98586.04	1534871**	1795778	354245
	(0.14)	(2.38)	(1.66)	(0.25)
R&D expenditures in % of GDP	1028526	-1224443	643680	51998.53
	(0.87)	(-1.09)	(0.84)	(0.08)
GDP per capita growth	164440.7	-20820.1	294763.8*	-19626
	(1.02)	(-0.12)	(1.96)	(-0.18)
Shock	**29365.19**	**25381**	**30376.08**	**22173.48***
	(1.14)	**(0.93)**	**(1.18)**	**(1.96)**
Constant	-13690.46	-10841.64	-5292.13	-10850,46
	(-0.86)	(-0.66)	(-0.61)	(-1.04)
Observations	48	48	45	45
R-sq	0.481	0.297	0.1951	0.1079

Table 11 reports the effect of a shock on amount invested in seed and start-up, with Denmark (dk) being a reference. The dependent variable is determined as $(Y_{i,t} - Y_{dk,t}), i = se, fi, no$ where Y is the amount invested in seed and start-up. Data is collected from EVCA. The table reports results from two separate panel data approaches, fixed effects and first differences. Model 1 shows the result from a fixed effects (FE) model without lag in the independent variables, while model 2 shows the results from a FE model with lag in the independent variables. Model 3 shows the results from a first differences (FD) without lag and model 4 illustrates the results from a FD model with lag. Yield-gov.bond is the yield on a 10-year government bond in the specific country. Market growth is the annual average return on the countries' market indices. Adjusted unemployment is the average annual unemployment rate in each country. R&D expenditure is the annual R&D expenditure in the country in percentage of GDP and GDP per capita growth is the annual growth of GDP per capita. All independent variables are determined as $(X_{i,t} - X_{dk,t}), i = se, fi, no$. In parentheses, we present the values of the t-statistics for each variable. First differences estimation is run with vca (robust) command in Stata, giving us slightly different significance levels compared to fixed effects. The t-statistics are significant at the following levels: ***p<0.01, **p<0.05, *p<0.1

Table 12. Invested amount, high-tech

	Fixed Effects		First Differences	
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Yield - gov.bond	-1492763	-3550387	1866947	-3833848
	(-0.39)	(-0.77)	(0.58)	(-1.07)
Market growth	74937.75*	78560.08	94698.28	125921.5
	(0.48)	(0.58)	(0.93)	(0.98)
IPO divestments	-2045.20	2296.47	2816.45	3210.09
	(-0.70)	(0.71	(0.75)	(1.28)
Adjusted unemployment	-1466405	194245	-7341566**	1915731
	(-0.86)	(0.12)	(-2.50)	(0.59)
R&D expenditures in % of GDP	3116985	-1551252	1299153	-2522479
	(1.13)	(-0.53)	(1.08)	(-1.49)
GDP per capita growth	1435993***	485780.2	906906.3**	499799.4
	(3.80)	(1.10)	(2.19)	(1.09)
Shock	**-45638.35**	**-17679.77**	**-49477.33**	**34006.82**
	(-0.76)	**(-0.25)**	**(-0.56)**	**(0.32)**
Constant	120198.6***	99913.65**	-10516.69	-10899.21
	(3.23)	(2.35)	(-0.48)	(-0.43)
Observations	48	45	45	45
R-sq	0.0305	0.1034	0.3088	0.1282

Table 12 reports the effect of a shock on amount invested in high-tech, with Denmark (dk) being a reference. The dependent variable is determined as $(Y_{i,t} - Y_{dk,t}), i = se, fi, no$ where Y is the amount invested in the high-tech sector. Data is collected from EVCA. The table reports results from two separate panel data approaches, fixed effects and first differences. Model 1 shows the result from a fixed effects (FE) model without lag in the independent variables, while model 2 shows the results from a FE model with lag in the independent variables. Model 3 shows the results from a first differences (FD) without lag and model 4 illustrates the results from a FD model with lag. Yield-gov.bond is the yield on a 10-year government bond in the specific country. Market growth is the annual average return on the countries' market indices. Adjusted unemployment is the average annual unemployment rate in each country. R&D expenditure is the annual R&D expenditure in the country in percentage of GDP and GDP per capita growth is the annual growth of GDP per capita. All independent variables are determined as $(X_{i,t} - X_{dk,t}), i = se, fi, no$. In parentheses, we present the values of the t-statistics for each variable. First differences estimation is run with vca (robust) command in Stata, giving us slightly different significance levels compared to fixed effects. The t-statistics are significant at the following levels: ***p<0.01, **p<0.05, *p<0.1

7.3 Tables, DD Sectors

Table 13 Number of companies invested in, high-tech vs. life science

	Fixed Effects		First Differences	
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Yield - gov.bond	631.79	-601.34	522.00	-335.54
	(0.45)	(-0.38)	(0.48)	(-0.27)
Market growth	23.61	-6.87	68.39	84.37
	(0.42)	(-0.15)	(1.19)	(1.23)
IPO divestments	3.44***	-0.77	3.87**	-1.17
	(3.24)	(-0.70)	(2.09)	(-0.68)
Adjusted unemployment	-334.14	115.82	-1005.81	1300.88
	(-0.55)	(0.20)	(-1.18)	(-1.24)
R&D expenditures in % of GDP	914.56	-1105.69	1410.00	-1078.48
	(0.92)	(-1.10)	(1.23)	(-0.88)
GDP per capita growth	56.46	72.87	83.85	31.97
	(0.41)	(0.48)	(0.82)	(0.32)
Shock	**60.63*** **	**-3.42**	**74.01*** *	**31.97***
	(2.79)	**(-0.14)**	**(2.11)**	**(1.90)**
Constant	35.97**	92.11***	1.43	-4.75
	(2.68)	(6.35)	(0.17)	(-0.53)
Observations	48	48	45	45
R-sq	0.2949	0.0063	0.2636	0.1860

Table 13 reports the effect of a shock on the difference in number of companies invested in, between high-tech and life science, with Denmark (dk) as a reference. The dependent variable is determined as $(Y_{i,t} - Y_{dk,t}), i = se, fi, no$ where Y is the difference in number of companies invested in between high-tech and life science. Data is collected from EVCA. The table reports results from two separate panel data approaches, fixed effects and first differences. Model 1 shows the result from a fixed effects (FE) model without lag in the independent variables, while model 2 shows the results from a FE model with lag in the independent variables. Model 3 shows the results from a first differences (FD) without lag and model 4 illustrates the results from a FD model with lag. Yield-gov.bond is the yield on a 10-year government bond in the specific country. Market growth is the annual average return on the countries' market indices. Adjusted unemployment is the average annual unemployment rate in each country. R&D expenditure is the annual R&D expenditure in the country in percentage of GDP and GDP per capita growth is the annual growth of GDP per capita. All independent variables are determined as $(X_{i,t} - X_{dk,t}), i = se, fi, no$. In parentheses, we present the values of the t-statistics for each variable. First differences estimation is run with vca (robust) command in Stata, giving us slightly different significance levels compared to fixed effects. The t-statistics are significant at the following levels: ***p<0.01, **p<0.05, *p<0.1.

Table 14 Number of companies invested, in high-tech vs. business and industrial products

	Fixed Effects		**First Differences**	
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Yield - gov.bond	-866.01	412.45	-20.96	288.366
	(-0.77)	(-0.35)	(-0.03)	(0.30)
Market growth	-8.63	-67.14*	60.76	5.20
	(-0.19)	(-1.94)	(1.64)	(0.12)
IPO divestments	2.28**	1.50*	2.14*	0.63
	(2.65)	(1.81)	(1.74)	(0.57)
Adjusted unemployment	-183.55	707.33	78.03	-384.48
	(-0.37)	(1.65)	(0.08)	(-0.45)
R&D expenditures in % of GDP	609.92	-1627.58**	587.74	-998.97*
	(0.75)	(-2.17)	(1.51)	(-1.74)
GDP per capita growth	140.43	28.15	94.08	-32.04
	(1.27)	(0.25)	(0.96)	(-0.45)
Shock	**35.06***	**21.70**	**50.31****	**29.14**
	(1.99)	**(1.19)**	**(2.63)**	**(1.62)**
Constant	22.94**	19.39*	-2.61	-6.67
	(2.11)	(1.79)	(-0.38)	(-1.01)
Observations	48	48	45	45
R-sq	0.5144	0.4611	0.1785	0.0887

Table 15 reports the effect of a shock on the difference in number of companies invested in, between high-tech and business & industrial products (BIP), with Denmark (dk) as a reference. The dependent variable is determined as $(Y_{i,t} - Y_{dk,t}), i = se, fi, no$ where Y is the difference in number of companies invested in between high-tech and BIP. Data is collected from EVCA. The table reports results from two separate panel data approaches, fixed effects and first differences. Model 1 shows the result from a fixed effects (FE) model without lag in the independent variables, while model 2 shows the results from a FE model with lag in the independent variables. Model 3 shows the results from a first differences (FD) without lag and model 4 illustrates the results from a FD model with lag. Yield-gov.bond is the yield on a 10-year government bond in the specific country. Market growth is the annual average return on the countries' market indices. Adjusted unemployment is the average annual unemployment rate in each country. R&D expenditure is the annual R&D expenditure in the country in percentage of GDP and GDP per capita growth is the annual growth of GDP per capita. All independent variables are determined as $(X_{i,t} - X_{dk,t}), i = se, fi, no$. In parentheses, we present the values of the t-statistics for each variable. First differences estimation is run with vca (robust) command in Stata, giving us slightly different significance levels compared to fixed effects. The t-statistics are significant at the following levels: ***p<0.01, **p<0.05, *p<0.1.

Table 15 Number of companies invested in, high-tech vs. energy and environment

	Fixed Effects		First Differences	
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Yield - gov.bond	-391.85	-39.07	22.82	386.05
	(-0.34)	(-0.03)	(0.03)	(0.39)
Market growth	-14.45	-91.35**	45.73	-11.37
	(-0.31)	(-2.65)	(1.14)	(-0.26)
IPO divestments	3.25***	1.76**	2.13	0.14
	(3.68)	(2.14)	(1.53)	(0.21)
Adjusted unemployment	504.46	1380.42***	733.78	297.71
	(0.99)	(3.23)	(0.82)	(0.35)
R&D expenditures in % of GDP	140.56	-1552.22**	111.41	-799.94
	(0.17)	(-2.08)	(0.22)	(-1.16)
GDP per capita growth	100.75	-19.25	115.66	-61.10
	(0.89)	(-0.17)	(1.25)	(-0.89)
Shock	**51.67*** **	**39.40** **	**53.25* **	**33.90**
	(2.86)	**(2.17)**	**(1.93)**	**(1.14)**
Constant	21.76*	20.90*	-3.25	-5.89
	(1.95)	(1.93)	(-0.49)	(-0.94)
Observations	48	48	45	45
R-sq	0.6803	0.6331	0.1931	0.1051

Table 17 reports the effect of a shock on the difference in number of companies invested in, between high-tech and energy & environment (E&E), with Denmark (dk) as a reference. The dependent variable is determined as $(Y_{i,t} - Y_{dk,t}), i = se, fi, no$ where Y is the difference in number of companies invested in between high-tech and E&E. Data is collected from EVCA. The table reports results from two separate panel data approaches, fixed effects and first differences. Model 1 shows the result from a fixed effects (FE) model without lag in the independent variables, while model 2 shows the results from a FE model with lag in the independent variables. Model 3 shows the results from a first differences (FD) without lag and model 4 illustrates the results from a FD model with lag. Yield-gov.bond is the yield on a 10-year government bond in the specific country. Market growth is the annual average return on the countries' market indices. Adjusted unemployment is the average annual unemployment rate in each country. R&D expenditure is the annual R&D expenditure in the country in percentage of GDP and GDP per capita growth is the annual growth of GDP per capita. All independent variables are determined as $(X_{i,t} - X_{dk,t}), i = se, fi, no$. In parentheses, we present the values of the t-statistics for each variable. First differences estimation is run with vca (robust) command in Stata, giving us slightly different significance levels compared to fixed effects. The t-statistics are significant at the following levels: ***p<0.01, **p<0.05, *p<0.1

Table 16 Amount invested, high-tech vs. life science

	Fixed Effects		First Differences	
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Yield - gov.bond	-4590692	-10000000	-4052508	-7346347
	(-0.41)	(-0.95)	(-0.45)	(-0.80)
Market growth	-79460.64	273261.1	29748.26	461954.7
	(-0.18)	(0.89)	(0.08)	(1.37)
IPO divestments	-5114.36	-14474.27*	28926.67	-24714.28
	(0.61)	(-1.97)	(1.65)	(-1.56)
Adjusted unemployment	4848651	5922416	-12900000	-7928509
	(-1.00)	(-1.55)	(-1.07)	(-0.78)
R&D expenditures in % of GDP	-4071518	1809227	-3864424	8874763
	(-0.51)	(0.27)	(-0.82)	(1.30)
GDP per capita growth	1332532	1752034*	479607.5	1472123
	(1.23)	(1.75)	(0.44)	(1.25)
Shock	**-196796.9**	**-161419.4**	**106275.3**	**-141142.8**
	(-1.14)	**(-1.00)**	**(0.45)**	**(-0.99)**
Constant	301681.6***	398332.7***	32463.7	-28351.96
	(2.83)	(4.13)	(0.42)	(-0.35)
Observations	48	48	45	45
R-sq	0.0271	0.1024	0.1469	0.2234

Table 14 reports the effect of a shock on the difference between amount invested in high-tech and life science, with Denmark (dk) as a reference. The dependent variable is determined as $(Y_{i,t} - Y_{dk,t}), i = se, fi, no$ where Y is the difference in amount invested between high-tech and life science. Data is collected from EVCA. The table reports results from two separate panel data approaches, fixed effects and first differences. Model 1 shows the result from a fixed effects (FE) model without lag in the independent variables, while model 2 shows the results from a FE model with lag in the independent variables. Model 3 shows the results from a first differences (FD) without lag and model 4 illustrates the results from a FD model with lag. Yield-gov.bond is the yield on a 10-year government bond in the specific country. Market growth is the annual average return on the countries' market indices. Adjusted unemployment is the average annual unemployment rate in each country. R&D expenditure is the annual R&D expenditure in the country in percentage of GDP and GDP per capita growth is the annual growth of GDP per capita. All independent variables are determined as $(X_{i,t} - X_{dk,t}), i = se, fi, no$. In parentheses, we present the values of the t-statistics for each variable. First differences estimation is run with vca (robust) command in Stata, giving us slightly different significance levels compared to fixed effects. The t-statistics are significant at the following levels: ***p<0.01, **p<0.05, *p<0.1.

Table 17 Amount invested, high-tech vs business and industrial products

	Fixed Effects		First Differences	
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Yield - gov.bond	-13100000*	6299784	-16900000**	5926119
	(-1.72)	(0.69)	(-2.32)	(1.04)
Market growth	-38990.01	274767.3	59272.21	264122.1
	(-0.13)	(1.03)	(0.19)	(1.24)
IPO divestments	-12779.51**	-5962.57	-2388.52	534.38
	(-2.22)	(-0.94)	(-0.21)	(0.08)
Adjusted unemployment	4811688	704769.8	-11000000**	8478562
	(-1.45)	(0.21)	(-2.36)	(1.24)
R&D expenditures in % of GDP	10000000*	-5111473	11200000***	-8619997***
	(1.85)	(-0.89)	(5.35)	(-2.79)
GDP per capita growth	2642583***	551590	1428060*	150735
	(3.57)	(0.64)	(1.71)	(0.21)
Shock	**20091.89**	**15167.29**	**223442.8**	**244675.2***
	(0.17)	**(0.11)**	**(1.57)**	**(1.69)**
Constant	117567.2	5138.54	3692.23	-312.58
	(1.61)	(0.06)	(0.08)	(-0.01)
Observations	48	48	45	45
R-sq	0.3020	0.0997	0.3098	0.1430

Table 16 reports the effect of a shock on the difference between amount invested in high-tech and business & industrial products (BIP), with Denmark (dk) as a reference. The dependent variable is determined as $(Y_{i,t} - Y_{dk,t}), i = se, fi, no$ where Y is the difference in amount invested between high-tech and BIP. Data is collected from EVCA. The table reports results from two separate panel data approaches, fixed effects and first differences. Model 1 shows the result from a fixed effects (FE) model without lag in the independent variables, while model 2 shows the results from a FE model with lag in the independent variables. Model 3 shows the results from a first differences (FD) without lag and model 4 illustrates the results from a FD model with lag. Yield-gov.bond is the yield on a 10-year government bond in the specific country. Market growth is the annual average return on the countries' market indices. Adjusted unemployment is the average annual unemployment rate in each country. R&D expenditure is the annual R&D expenditure in the country in percentage of GDP and GDP per capita growth is the annual growth of GDP per capita. All independent variables are determined as $(X_{i,t} - X_{dk,t}), i = se, fi, no$. In parentheses, we present the values of the t-statistics for each variable. First differences estimation is run with vca (robust) command in Stata, giving us slightly different significance levels compared to fixed effects. The t-statistics are significant at the following levels: ***p<0.01, **p<0.05, *p<0.1.

Table 18 Invested amount, high-tech vs. energy and environment

	Fixed Effects		First Differences	
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Yield - gov.bond	1472235	132840.3	4059031	-2436025
	(0.28)	(0.02)	(0.89)	(-0.60)
Market growth	151927.8	-37060.21	162251.1	35021.82
	(0.72)	(-0.22)	(1.44)	(0.21)
IPO divestments	1851.47	4920	2156.36	3226.09
	(0.46)	(1.20)	(0.48)	(1.21)
Adjusted unemployment	1439559	2921848	-8384639*	1794801
	(0.62)	(1.38)	(-1.81)	(0.43)
R&D expenditures in % of GDP	4115237	102007.3	1584143	-1935928
	(1.09)	(0.03)	(0.96)	(-1.10)
GDP per capita growth	1444413***	629597.8	726842.1	743968.2
	(2.81)	(1.13)	(1.35)	(1.01)
Shock	**42081.2**	**55472.6**	**-88627.27**	**-16786.68**
	(0.51)	**(0.62)**	**(-0.78)**	**(-0.14)**
Constant	-14876.07	-38854.78	-23993.62	-17884.99
	(-0.29)	(-0.72)	(-0.87)	(-0.54)
Observations	48	48	45	45
R-sq	0.2599	0.3093	0.2225	0.092

Table 16 reports the effect of a shock on the difference between amount invested in high-tech and energy & environment (E&E, with Denmark (dk) as a reference. The dependent variable is determined as $\left(Y_{i,t} - Y_{dk,t}\right), i = se, fi, no$ where Y is the difference in amount invested between high-tech and E&E. Data is collected from EVCA. The table reports results from two separate panel data approaches, fixed effects and first differences. Model 1 shows the result from a fixed effects (FE) model without lag in the independent variables, while model 2 shows the results from a FE model with lag in the independent variables. Model 3 shows the results from a first differences (FD) without lag and model 4 illustrates the results from a FD model with lag. Yield-gov.bond is the yield on a 10-year government bond in the specific country. Market growth is the annual average return on the countries' market indices. Adjusted unemployment is the average annual unemployment rate in each country. R&D expenditure is the annual R&D expenditure in the country in percentage of GDP and GDP per capita growth is the annual growth of GDP per capita. All independent variables are determined as $(X_{i,t} - X_{dk,t}), i = se, fi, no$. In parentheses, we present the values of the t-statistics for each variable. First differences estimation is run with vca (robust) command in Stata, giving us slightly different significance levels compared to fixed effects. The t-statistics are significant at the following levels: ***p<0.01, **p<0.05, *p<0.1.

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