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Venture Capital and Industry Specialization

An empirical study of venture capital investments in Norwegian portfolio companies

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Abstract

Applying a carefully constructed data sample of 120 Norwegian portfolio companies being backed by Norwegian Venture Capital firms, this thesis aims at answering how the degree of industry specialization in Venture Capital firms affects the performance of portfolio companies. This thesis applies three different measures of industry specialization, in which two are derived from the literature on corporate diversification. Further, the thesis also explores the effects of specialization at different industry levels. Lastly, having access to detailed accounting information on Norwegian portfolio companies allows us to analyse detailed performance measures in different time windows, by considering A) Increase in profits, B) Increase in revenues, C) Revenue growth, D) Payroll growth and E) Productivity growth.

We provide evidence of a positive relationship between the industry specialization of a Venture Capital firm, and performance in portfolio companies. Considering specialization at different industry levels, we find that industry specialization has a positive effect on the performance of portfolio companies when Venture Capital firms specialize at industry section level, and have portfolios with more than 40% of the investments in the same industry section. We find that there is a positive effect from industry specialization if Venture Capital firms invest in their preferred industry section, and a negative effect of industry specialization when Venture Capital firms invest outside their preferred industry section.

Contents

Preface

With this thesis, we complete our Masters of Science in Economics & Business Administration at the Norwegian School of Economics (NHH).

Working with this thesis has been challenging but yet outmost rewarding. During the process, we have gained interesting insight into the Norwegian venture industry and acquired valuable programming skills in Stata.

First, we would like to thank our supervisor, Lasse Lien, for invaluable guidance and support during the process of writing this master thesis. We consider his knowledge, inputs and enthusiasm towards the thesis as highly motivating. In addition, we will like to thank Associate Professor Carsten Bienz for providing us with data on private equity deals. We would also like to express our gratitude to the SNF institute, represented by Kellis Akselsen, for granting us access to their database of Norwegian accounting data.

1. Introduction

In 2001, Microsoft was the only technology company out of the top five publicly traded companies by market capitalization. The other four were more traditional companies, such as General Electric, Exxon, Citi Bank and Walmart. Today, only 16 years later, these four have been surpassed by Apple, Google, Amazon and Facebook – technology companies which were either small or did not exist at all in 2001. Key to these companies is the presence of venture capitalists, able to raise capital for risky and uncertain ideas.

Many industrialized countries face aging populations as well as declining productivity growth. One proposed solution emphasizes innovation and entrepreneurship. In order to reduce the increasing gap between forecasted costs and revenues on the national accounts, some politicians and economists recommend increasing the level of innovation in the economy.

Venture capital (VC) plays a vital part in creating an innovative economy (Lerner, 2009). Venture capital funds are investment vehicles managed by general managers, i.e. the venture capitalists. VC funds invest in early-stage ventures such as start-ups and small growth companies, which after a VC entry*,* i.e. an investment, is named a Portfolio Company (PC). New companies depend on venture capital to spur further growth. In the literature, much attention is devoted to the effect venture capital plays in the growth of a company. To the authors' knowledge, less attention is given to the *owner competencies* of a venture capitalist, and whether these competencies affect portfolio companies' performance. One factor found to influence the owner competencies of VC firms is the degree of *industry specialization*. Considering the rapid growth of technological industries, as well as more access to VC, it is interesting to understand if VC specialization affects the performance of these companies. In this thesis, we address this question by analysing differences in portfolio company performance resulting from varying degrees of industry specialization. ***Does industry specialization affect the performance of portfolio companies?***

We conduct an empirical analysis of the effect of industry specialization in venture capital firms on portfolio companies. Our data sample contains 120 Norwegian portfolio companies that are backed by Norwegian venture capital firms. To test effects, we use three different measures of industry specialization: 1) the *degree of related specialization, 2) portfolio relatedness* and 3) *industry level specialization.* Drawing on the findings of Gompers et al.

(2009), we examine whether the performance of specialists vary when investing in preferred industries and not. We do this by including an interaction term measuring the combined effect of being a specialized VC firm investing in a preferred industry section. This enables us to analyse if the effects of industry specialization on PC performance depends on the industry of the PC in question.

In the literature, Gompers et al. (2009) find that there is a positive effect of industry specialization on portfolio company success, and that this is more important at the level of individual venture capitalists than on the VC firm level. Moreover, the benefits of specialization at the firm level support the idea of value adding activities or information asymmetries resulting in enhanced performance, more than outweighing the benefits of diversification.

In the finance literature, many studies investigate the relationship between VC industry specialization and company performance by using broad industry classifications (see Gompers et al. (2009) and Matusik and Fitza (2012)). One of the weaknesses related to these studies is that the industry classes chosen are too broad to capture the effects of industry specialization.

The literature on corporate diversification (Caves et al., 1980; Sharma, 1998) uses more detailed categorizations of the differences between companies. For instance, Caves et al. (1980) present the concentric index of related diversification. The concentric index is part of the literature concerning corporate diversification, and take into account different industry levels when calculating a diversification score. In this thesis, we use a measure of industry specialization based on the concentric index to assign the *degree of related specialization*. Thus, we use the methodology from the literature on corporate diversification when studying the performance of portfolio companies.

In order to answer the question of how industry specialization of VC firms affects the performance of PCs, we define the following research questions: i) How does related specialization within a VC firm affect the performance of portfolio companies? ii) How does a VC firms' specialization at a given industry level affect the performance of PCs? iii) How does the combined effect of related and industry level specialization of a VC firm affect the performance of PCs?

The thesis contributes with several findings of interest related to the effects of industry specialization among VC firms on PC performance. First, we find evidence suggesting a positive relationship between industry specialization in a VC firm and the performance of PCs. This is in line with Montgomery and Wernerfelt (1988), who argue that more specific resources have higher rents than less specific resources when applied in an industry close to the industry in which the resources originated. Furthermore, VC firms with a high degree of related specialization have higher performance as the VC has more specific resources applicable to the PC. Second, industry specialization seems to have a positive effect on the performance of PCs when VC firms specialize at NHO level, and have portfolios with more than 40% of the investments in the same NHO as the PC invested in. Our finding gains support from the findings of Gompers et al. (2009), who found that the performance of specialized VC firms appears to be better in general. They define specialization as the ratio of all previous investments undertaken by the VC firm in a certain industry, to all previous investments irrespectively of industry. Third, we find that there is a positive effect from industry specialization if VC firms invest in their preferred NHO, and a negative effect of industry specialization when VC firms invest outside their preferred NHO. This is in line with the theory presented by Montgomery and Wernerfelt (1988) theorizing that specific resources will have lower rents than of less specific resources when the resources are used far from the industry in which they originated.

The thesis is structured as follows. Chapter 2 introduces relevant theory and literature addressing ownership, and the effect of industry specialization within venture capital firms. Chapter 3 provides an overview of the data sources used in this thesis, and explains the data sampling process. Chapter 4 describes the empirical and theoretical foundation of the thesis. In addition, the various variables included in the regression models will be carefully described. Next, we conduct the regressions models, and present and discuss the results from these in Chapter 5. Last, we conclude in Chapter 6.

2. Theory

In the following, we discuss the importance of ownership for both firms and society at large, through which channels ownership might affect the performance of companies and how this ownership effect is affected by the degree of industry specialization of the venture capital firm. We present findings from similar studies before presenting our research questions. The research questions are developed based on theories concerning the role of ownership, information asymmetries and theories being part of the resource based view on competitive advantage.

2.1 Why Does Ownership Matter?

Ownership plays a crucial role in the reallocation of capital in a market economy. Through this function, owners take part in the competitive dynamics of an economy, which refers to the reallocation of inputs and outputs among firms as a result of competition (Foss & Lien, 2010; Lien, 2005). Common for these views are that they treat owners as a homogenous group all being able to identify the best theory of value creation for the assets they own. Rather than discussing how owners may affect the value propositions of their assets, one discusses how owners may use incentives to align interests among themselves and their managers, and the boundaries of the firm.

Foss and Lien (2010) argue that ownership does affect the market process and industry dynamics, and that one of the roles ownership plays in the market process is to *ease the process of commercial experimentation.* They argue that ownership contributes to entrepreneurship through its ability to reallocate ownership from less competent to more competent owners. The market for corporate control allows for this reallocation of control rights.

This role of ownership is possible if owners differ in their talents as owners (Alchian, 1965). The view on ownership presented in the Austrian school of economics, in particular by Ludwig von Mises (1949), allow for these differences in talents by allowing capital goods to be heterogeneous. In the Misesian appraisement theory of entrepreneurship (Mises, 1949; Salerno, 1999) productive ventures may require “skilled foresight” into which combinations of heterogeneous capital goods that best will meet the future, yet non-existent demand (Foss & Lien, 2010).

Misesian appraisement theory of entrepreneurship (Mises, 1949; Salerno, 1999) states that ownership contributes to competitive dynamics through allowing owners to differ in their competencies as owners (Foss & Lien, 2010). Lien (2005) separates these competencies influencing the effect of ownership on company performance in three distinct parts. First, ownership functions as *fuel* for the firm in question in terms of access to capital. Second, owners may provide access to complementary resources otherwise too costly or inaccessible for the portfolio company, that enhance the performance of the unit. Lastly, owners contribute to competitive dynamics through screening ideas, managers and firms.

The function of owners contributing to competitive dynamics through *fuel* can be divided into two parts, the financing of risky ideas and improved selection of investments. The more general and overarching role of financing of risky ideas is defined by how equity financing differs from credit financing concerning uncertainty and risk. Creditors hold rights to the amount lent and interest, protecting the creditors from losing everything if the venture goes into bankruptcy. The downside is that creditors do not hold any rights to the upside if the venture is successful. In a system allowing for limited liability, ownership through equity does provide rights to the upside and protection from the downside except for the equity invested. Nevertheless, it does not provide rights to assets in case of bankruptcy, thus having a higher risk than credit. Equity owners take part in the upside if a venture is successful, balancing the higher risk with the prospect of higher returns. Thus, equity ownership enables risky ventures that drive innovation and competitive dynamics.

The other function of owners in terms of their function to *fuel* company performance is through an improved selection of investments. Owners differ in their ability to choose which firms to invest in. When encountering an investment opportunity, the investor uses his/her screening abilities to decide whether to invest in the company or not. This is the capital allocation mechanism which ideally should reallocate capital from low to high productivity applications. By allowing owners/investors to differ in their abilities to perform the screening activities, and assuming an efficient market for corporate control, the owners best able to contribute to value creation will gain control over the resources. These dynamics will result in the economy benefitting from having more capable owners through increased productivity (Foss & Lien, 2010)

In resource based theory (Barney, 1991; Wernerfelt, 1984) the competitive advantage of a firm is the result of the resources available to the firm. The theory states that some resources are more important for the competitiveness of the firm than others. Competitive advantage may derive from both controlling a resource that in its own is rare, valuable, imperfectly imitable and non-substitutable (VRIN), or from controlling a "basket" of resources that through complementarity results in a combined resource that meets the VRIN criteria. Mises (1949) presents a similar view on the importance of resources for the performance of companies. He argues that some owners are more suited than others for different companies' dependent on the complementarity of the resources of the owner and the investee. The provision of resources through ownership can be divided into two parts, sharing of resources controlled directly by the owner, and sharing of resources between different investees. These two parts will be treated individually in the following paragraphs.

The owner may possess resources that can be shared directly from the owner to the investee. Such resources are among others knowledge, networks outside the portfolio of investments and other kinds of non-financial resources. An owner that has considerable experience being an owner of retail stores will be able to provide industry insight, knowledge and experience to a young retail store in which he is invested. If this knowledge related to the industry and activities of the investee is not evenly distributed among owners, this resource may contribute to a competitive advantage. Another resource that owners may share directly with their investees are networks (Hochberg, Ljungqvist, & Lu, 2007). Some well-connected owners may be able to provide access to regulators, suppliers and customers otherwise out of reach for the investee. As the quality of an owners' network depends on characteristics of both the investee and the owner, it is a reasonable assumption that effects of this resource differ across owners.

The other channel through which owners may provide complementing resources to their investees are through interactions and resource sharing among the portfolio of investees. Individual firms may be part of a portfolio of companies that combine, share and pool resources otherwise unavailable because they are under common ownership (Foss & Lien, 2010). Kuppuswamy, Serafeim and Villalonga (2014) find that internal labour and capital markets are more efficient than external markets in presence of frictions in external markets. One may argue that firms united by common ownership do possess internal factor markets. The owner of multiple firms may relocate employees from one firm to another, or use the profits from one firm to finance investments in other firms in the portfolio. Such markets may reduce costs compared to external markets due to information asymmetries and the missing ability to create perfect contracts (Kuppuswamy, Serafeim, & Villalonga, 2014). Sharing of resources among firms under common ownership is also less time consuming than to accumulate the resources in the firms individually.

The third way owners may contribute to competitive dynamics is through their screening activities. Screening activities refer to the ability of owners to assess the potential value of an asset through identifying its best use both today and in the future. Owners are thought to have heterogeneous abilities to screen ideas and managers (Foss & Lien, 2010). There are two different situations in which the screening abilities of owners are important. One is how owners may differ in their ability to detect misuse of assets today, the other relates to future misuse of the assets.

Owners with a relatively greater ability at screening may be better to identify misuse of their assets than other owners. As incentives might divert between owners, managers and employees, owners may experience investees behaving in ways not beneficial to the owner. (Jensen & Meckling, 1976). The costs of agency problems can be reduced by competent screening. The screening will have an effect both by identification of misuse of a firm`s resources, and by the mere threat posed on agents of detection. If owners were not capable of screening the activities of their investments, the reallocation of resources and improvements in management would be less efficient (Foss & Lien, 2010).

Owners with a relatively better screening ability than other owners will be able to better predict the future. Through the ability to better infer meaningful predictions from information available to them, the more able owners will be more successful estimating outcomes in the future. Owners can be better at identifying potential benefits from changes to a firms´ strategy, i.e. through the need for investments in new technologies or the need to enter a completely new line of business.

From the theories presented in this section, we find that ownership has a role in the competitive dynamics of the economy due to its heterogeneity with respect to differing capabilities concerning *fuelling*, *complementing* and *screening* activities. These theories state that ownership matter because owners differ in their talents as owners, and that the allocation of the “right” owners to the fitting resources will lead to productivity growth.

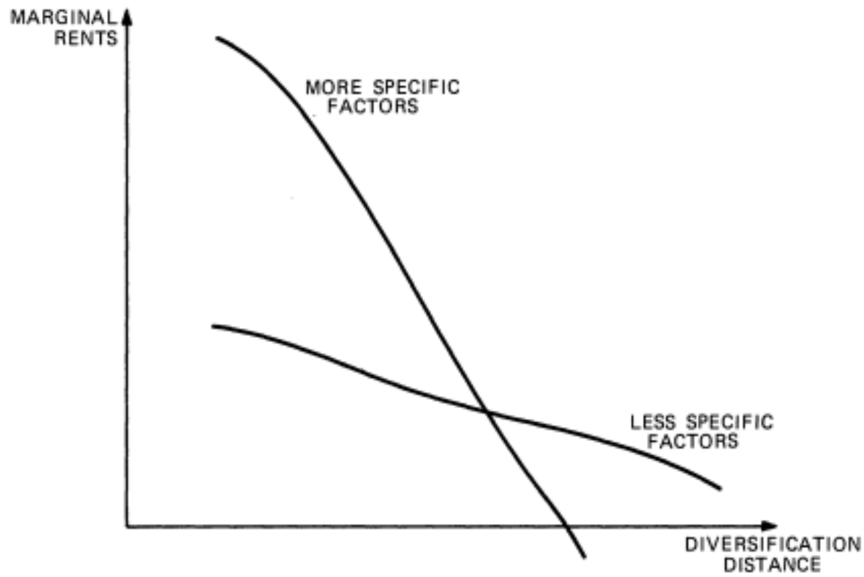
2.2 Why Does Specialization of Ownership Matter?

Based on the channels through witch Mises (1949) argues that ownership influence competitive dynamics we will in the following discuss the implications of owners having different degrees of industry specialization. Throughout the discussion, we will answer the question of to what extent the effects of specialization are likely to manifest themselves through owners having an enhanced ability to invest in the most promising companies, selection, or through the ability to add value through interactions with the firm, i.e. the treatment effect of ownership.

Lien (2005) argues that providing access to capital, or *fuel,* is one of the most central ways in which owners can contribute to competitive dynamics. Will owners' ability to invest vary with the degree of industry specialization? And will this influence the value creation within the firms? Capital, measured in monetary terms, is not affected by the source of the funds, regardless of the investor's skills nor other attributes. Thus, if all other features of the investee are identical, the effect of capital stemming from a specialist should be no different from the effect of capital stemming from a generalist. There does not seem to be any benefits regarding the value creating abilities of the investee regarding the source of funding. However, it may be the case that specialists and generalists differ in their preferences regarding investment opportunities. Given that specialists must invest most their capital within a single industry, their portfolio has a lot more idiosyncratic risk than a diversified portfolio (Sharpe, 1964). The effect of specialization on access to capital will in this way be affected by the riskiness of different investment strategies, in which owners should choose diversified portfolios to reduce the amount of idiosyncratic risk affecting their investments. On the other side, more specialized investors may have better abilities choosing witch firms to invest in. Specialized investors may have access to information not available to generalist investors due to spending more of their efforts on few rather than many industries. They may also be better at interpreting this information due to experience in interpreting information from the industry in question. The cumulative effect of industry specialization on the owners´ ability to *fuel* competitive dynamics depends on the relation between the negative effect stemming from reduced diversification of risk and the positive effect from improved ability to choose better investments. If investors are rational, one should increase the degree of specialization until the marginal utility equals the marginal cost. We are not able to decide at what degree of specialization this takes place from a theoretical view. Anyhow, the effect of industry specialization on the owners' ability to *fuel* competitive dynamics is one of selection.

Does the degree of industry specialization affect the competitive dynamics through the channel of *complimenting* resources? The answer to whether a specialist has an advantage over generalists related to providing access to complimentary resources to its investees lies in the answer to whether specialized resources has a larger effect on competitive advantage than more general resources. Wernerfelt and Montgomery (1988) argue that the rents to different factors depend on them being more or less specific. Factors, or resources, that are specific to one industry gains higher rents than less specific factors that may be deployed in multiple industries. Specific factors have higher rents in markets closer to the originating market, whilst less specific have higher rents than more specific in markets further from the originating market.

Figure 2.2.1: Hypothesized relationship between diversification distance and marginal rents for different degrees of factor specifity



Source: Montgomery, C. A., & Wernerfelt, B. (1988). Diversification, Ricardian rents, and Tobin's q. *The Rand journal of economics*, 623-632.

Based on the theory presented by Wernerfelt and Montgomery (1988) one may argue that complimenting the resources of a firm with resources specific for the industry in which the firm operates yields higher effect on the firm`s competitive advantage than complimenting the firm`s resources with more general resources. This supports the intuition that owners having more in-depth knowledge, longer industry experience and more complete networks within the industry are able to provide more valuable resources to the investee. However, if the complimenting resources of the owner are specific to an industry far from the industry of the investee, the model presented by Wernerfelt and Montgomery (1988) predicts that the effect on the firms´ competitive advantage will be less positive than the effect would have been if the owner possessed less specific resources. The performance of firms depends on the degree of specialization of the resources possessed by the owner.

The ability of the owner to compliment the investees' resources do depend both on the resources the owner possesses on his/her own hand and the resources possessed by the firms in which he/she is invested. Following the arguments made by Wernerfelt and Montgomery (1988) portfolios with less related diversification, i.e. a more specialized portfolio, will have higher performance. Firms in specialized portfolios will have the opportunity to share resources that are specific to the industry in which the portfolio companies operate, and thus have higher rents to the use of these resources than they would have from specific factors not relevant to their industry or from less specific factors. This sharing of resources do not depend on the resources possessed by the owner directly such as the owner's knowledge or experience. It depends on the knowledge and experience of other firms under the same ownership. An example of such sharing is a biotechnology firm being owned by an owner that is specialized in biotechnology and health technology. We find it plausible that this biotechnology firm will benefit more from sharing resources with such a portfolio of companies than one specialized in biotechnology and oil & gas. As resources specific to biotechnology firms are more rare than analytic resources, it is also likely that the rents to those resources are higher than for a more general resource such as analytic abilities.

The third channel in which characteristics of the owner may affect the productive dynamics of markets is through *screening*. Will owners differ in their ability to perform screening dependent on their degree of industry specialization? Screening affects both the choice of whether to invest and the choices regarding the use of assets when already owning a firm. Whilst the ability to choose the right investments is a selection effect, the ability to detect suboptimal behaviour of managers and misuse of resources is a treatment effect of screening.

The ability to perform screening activities depend on an owner's ability to understand the nature of the businesses in which he/she holds interest. This ability depends in turn on the owners´ access to information relative to other potential owners, and his/her ability to interpret the information relative to other potential owners. It is difficult to assess whether owners with a high or low degree of industry specialization will have better access to, and ability to interpret, information relevant for the screening of the firms. Favouring the more specialized owners one may argue that they have access to more information due to closer ties with the industry, that they are able to use more of their time and efforts acquiring new knowledge about the industry and that their experience interpreting information about that single industry has trained them such that they have a greater ability to interpret this information. On the other hand, favouring the less specialized owners one may argue that the ability to predict future outcomes depends not only on knowledge concerning an industry within the industry boundaries drawn today, but also on information concerning the industry given the industry boundaries of tomorrow. By having access to information from a broad spectre of industries the less specialized owner may detect trends that are likely to affect multiple industries. As technological changes reach different industries at different points in time, a generalist may use the experience regarding the introduction of a new technology in one industry in another. Another argument in favour of the less specialized owners is that in case of changes over time affecting industry boundaries, the less specialized owner has training in interpreting information from a broad spectre of industries.

In sum, our discussion suggests that there might be benefits to industry specialized ownership. With regards to the *fuel* mechanism, the benefits of diversification through reduction of idiosyncratic risk speaks against industry specialized ownership, whilst the increased ability to choose which firms to invest in speaks for industry specialization. Regardless of direction of the total effect, the effect is one of selection. Concerning *complementing* resources, we find support for a positive treatment effect of specialization through the effect of more specific factors yielding higher rents when put into use in markets close to the market in which the resource originated. Finally, the effect of the *screening* capabilities of owners affects portfolio companies through the owner's ability to perform activities such as guidance and governance, i.e. treatment effects. There is no clear direction of the effect of industry specialization of ownership on the *screening* capabilities of owners.

2.3 Why Industry Specialization Matters to Venture Capital Firms

Venture capital firms are interesting subjects for studies aimed at exploring the role of ownership on company performance and other outcomes. On one hand, the venture capital firm is in itself an interesting vehicle for diversification of risk and exercising of the control rights to the portfolio companies in which they are invested. In addition to this, the clearly defined investment horizon, the delegation of control rights to the general managers of the venture capital funds and known preference related to outcomes, i.e. a successful exit by IPO or acquisition, makes the VC firm an interesting research subject. We will in the following present some of the literature related to industry specialization of venture capital firms before presenting the research questions for our analysis.

Gompers, Kovner and Lerner (2009) find a strong positive relation between the degree of industry specialization and portfolio company performance measured as successful IPO´s, both for individual venture capitalists and at the firm level. They argue that the poorer performance of generalists appears to be caused by both an inefficient allocation of funding across industries and poor selection of investments within industries. The study also tests the marginal effect of firm industry specialization when controlling for the degree of specialization of the individual venture capitalist. The effect of increasing firm specialization decrease when controlling for individual traits. This supports the assumptions regarding the effects regarding the screening abilities and the venture capital firm's complementary resources depending on the venture capitalist's abilities.

Matusik and Fitza (2012) finds a U-shaped relationship between portfolio company success and Venture Capital firm industry diversification when studying a sample of 7.479 portfolio companies. This finding suggests that both industry specialization and diversification have positive effects on portfolio company performance. They state that "*Especially in the context of increased uncertainty (e.g., early stage investing), firms benefit from either specialization or diversification; those firms who cannot reap the benefits of specialization or high diversification have relatively poor performance.*" (Matusik & Fitza, 2012).

In a study on US venture capital funds, Bartkus and Hassan (2009) find no statistically significant relationship between industry specialization and portfolio company success as measured by the number of IPO´s. However, they find a positive effect on performance from stage specialization. They compare the effects of the relatively least specialized and most specialized companies, defined as the lower and upper quartiles of their observations.

The studies conducted by Bartkus and Hassan, and the one by Matusik and Fitza seem to draw different conclusions. However, the study by Bartkus and Hassan only takes the upper and lower quartiles of venture capital firms and studies a linear relationship between the variables. The result is in line with the finding by Matusik and Fitza. Due to the non-linear relationship between industry specialization and portfolio company performance, one expects to find equal performance of the least and most specialized companies.

The results of the above mentioned studies differ in their findings related to the effects of industry specialization on portfolio company performance. Based on the theories presented, and the empirical designs used in the above mentioned studies we will continue with the three following research questions:

2.4 Research Questions

Research question I

How does the related specialization of a Venture Capital firm affect the performance of portfolio companies?

Research question II

How does a Venture Capital firms´ specialization at a given industry level affect the performance of portfolio companies?

Research question III

How does the combined effect of related and industry level specialization of a VC firm affect the performance of portfolio companies?

3. Data and Possible Biases

This chapter is structured in the following way; First, this chapter will briefly describe the different sources of data used in this thesis. Second, we will provide a walkthrough of the process resulting in the data sample being used in the analysis. Third, we discuss possible biases resulting from the selection and the nature of our final data sample.

3.1 Sources of Data

The analysis in this thesis is primarily based on data from two different sources, namely i) transaction data from the database of Argentum Centre for Private Equity (ACPE) and ii) accounting data for Norwegian companies, provided by the Centre for Applied Research at NHH (SNF) (Berner, Mjøs, & Olving, 2016). The ACPE database contains information on private equity deals from 1992 – 2012, including, among others, names of private equity firms and portfolio companies, time of investment, and investment stage. The ACPE database is structured in excel, and contains several different excel sheets in which each provides different types of information related to private equity deals. The SNF accounting database, contains accounting data and company information from all private and public Norwegian companies in the period from 1992 to 2015.

3.2 Constructing the Data Sample

This section provides a walkthrough of the process resulting in the data sample being used in the analysis. At the end of each subpart, we provide summaries of the enumerated steps, including the effect on the sample size. These summaries also display the sample size at the different steps.

3.2.1 Retrieving Transaction Data From the ACPE Database

This sub-section will describe the process of retrieving data related to venture transactions from the ACPE database.

1) Creating a data sample including venture classified investments in Norwegian PC, by Norwegian VC firms.

In order to obtain information about VC investments we were given access to the ACPE database. As this database only contains information up until 2012 we were also granted access to updated data, covering information of Norwegian private equity deals up until 2015. This information is also compiled by the ACPE. Seeking to retrieve the largest data sample possible as our point of departure, we merged the updated information on Norwegian venture transactions with the ACPE database in excel. We proceeded retrieving data from the ACPE database requiring various criteria to be met. First, as this thesis aims to explore the effect of specialization of venture capital firms, we limit our research to only consider investments being classified as venture capital transactions. Second, we choose to only focus on Norwegian PCs, as including foreign PCs requires normalization of accounting data across numerous countries which is considered not to be feasible given the time frame of this thesis. Third, we choose to limit our data sample to only contain VC firms headquartering in Norway. Including foreign VC firms introduce several concerns, among others, the fact that we have little insight into their investments in non-Norwegian PCs. Hence, we will not be able to assess the degree of specialization for these VC firms. Using these three main criteria we were able to retrieve 733 transactions from the ACPE database. It is worth nothing that these transactions include all venture transactions in Norwegian PCs irrespectively of investment round. Of these transactions, there were many observations that did not contain information on what year the investment took place, and some did not contain the organization number of the PC. These are both necessary information for the analysis.

2) Increasing the data sample by adding collected information regarding investment year in PCs.

As the data sample contained observations without information on investment year, a great effort was made supplementing the data sample with this information for some of these observations. The ACPE database contains several excel sheets in which contains different information. This implies that the same transaction can be registered with information on investment year in one excel sheet and without in another. By using the VLOOKUP function in excel we searched through the other excel sheets in the database in order to detect more information on investment year.

In pursuance of enlarging the number of observations further, we also used several external sources of information. Seeking to amplify the information on year of investment we focused on the observations containing all necessary information apart from investment year. We started by contacting Gjermund Grimsby in Menon Economics. They have access to a database of private equity deals compiled by the European Venture Capital Association (EVCA). He was not allowed to share this database with us, but advised us to contact the Norwegian Venture Capital Association (NVCA) in order to get access to the EVCA database. However, after numerous phone calls and emails, we were not permitted access to the database. Still, with high hopes of adding information on missing investment years to the data sample, we sent out emails to all of the general partners in the different VC firms in the data sample. We added a list of all the transactions undertaken by each of the VC firms in which we did not have the year of investment. To our disappointment, only one VC firm, Maturo Capital, came back to us.

Some VC firms have listed their portfolio of PCs on their website, in which some provides information on the time of investment. Going through these we were not able to find any information on investment year not already included in the ACPE database. However, using Wayback Machine, which is a library of websites allowing the user to retrieve saved historic information, which has been removed from the web page today, we identified several transactions including investment year. At last, we also went through numerous of different databases searching for each of the transaction with missing information on investment year. Through, Crunchbase[1], CB Insights[2], and Zephyr[3] we were able to identify several transactions containing years of investments. From the process described in step 2, we managed to add 50 observations to the data sample.

3) Increasing data sample by adding collected information regarding organization number of PCs.

In order to find information on organization numbers we used the two sources regnskapstall.no and proff.no. Through these channels, we were able to add the organization number to 5 of the observations in the dataset.

[1] Crunchbase is an open source database containing information on both investments and companies.

[2] CB Insights is a market intelligence platform containing deal data on venture capital transactions. The database can be accessed through subscription.

[3] Zephyr is a database containing comprehensive deal data and detailed company information operated by Bureau van Dijk, a Moody´s Analytics Company. The database can be accessed through NHH´s subscription.

4) Increasing data sample by adding collected information regarding investment stage.

The excel sheet in the database that we used as our main source of information contained numerous of transactions in which was not registered with information on investment stage. However, as the database contains several different excel sheets each providing different overviews of transactions we used the same method as we did when searching for information on investment year, namely using the VLOOKUP function in excel. Combining the information from the different excel sheets we were able to identify 113 new transactions classified as venture.

5-6) Removing observations with missing organization number or investment year.

By removing all observations with missing information on either organization number or investment year our data sample were severely reduced. However, we would like to pinpoint the fact that many of these observations are not first round investments, implying that we do not lose 402 unique PCs.

7) Removing all the duplicates.

As we amplify our main data source from the ACPE database with updated information on Norwegian transactions we end up with 142 transactions being listed twice. Hence, we remove these duplicate observations.

8) Removing later rounds of investments.

There are some PCs in which receives several rounds of funding. This could either be from the VC firm who has already invested in the firm, or from a different VC firm. In this study, we seek to analyse the effect that appears after the first investment in the PC. We attribute the promising performance, resulting in new rounds of investments in a PC, to the VC firm that first invested in the PC. Thus, we treat later investments as treatment effects of the first investment. We remove these observations, as we in this study only analyse the effect of first-round investments. Doing this we remove 62 observations.

9) Removing same company being registered twice.

When scrutinizing our observations, we discovered that 16 of the same business entities where registered twice. In other words, registered with two different names and two different organization numbers. To exemplify, we discovered examples of the same PC both being listed as a stock-based company (AS) and not, and some being listed as a division in addition to a regular company. Further, we also found examples of PCs being listed as a holding company in addition to their regular company. By using sources as regnskapstall.no and proff.no, we investigated these cases further and ensured that we only where left with the observations representing the operating part of the PCs.

10) Removing observations in which the VC firm is not the most specialized among the joint venture partners.

In the case of a PC being backed by a joint venture, we had to decide what specialization score to assign to the PC. We considered two methods. i) Compute the specialization score for each of the VC firms in the joint venture and calculate the average score. Similar approach was used by Gompers et al. (2009) who calculated an average HHI[4] score of all venture capitalist in a VC firm to measure specialization. ii) Assign the specialization score of the most specialized VC firm to the PC. We considered approach ii as the most appropriate for our purpose. We seek to analyse the effect of the industry specialization of VC firms on PC performance. Thus, if a PC has access to a VC firm with industry specialization, we want to measure if this affects the performance in the PC. We find that the first approach is not applicable to our case as it will neglect this. Further, approach i assumes that the average specialization score reflects the joint degree of specialization of the VC firms. In our opinion, being backed by a specialized VC firm and a generalist VC firm is not equivalent of being backed by a VC firm being neither of the two. Based on this we keep the observations including the most specialized VC firm in the joint venture and remove those who are not. This results in 22 observations being removed.

Table 3.2.1 provides an overview of the procedure resulting in the data sample from the ACPE database.

[4] The Herfindahl-Hirschman Index. It was originally used to measure market concentration. It has later also been used to assess specialization.

Table 3.2.1: Overview of the process constructing the data sample

Step	Description	Effect	Sample size
1	Venture classified investments in Norwegian PC, by Norwegian VC firms, from the ACPE database		733
2	Increasing data sample by adding collected information regarding investment year in PCs	+50	783
3	Increasing data sample by adding collected information regarding organization number of PCs	+5	788
4	Increasing data sample by adding collected information regarding investment stage	+113	901
	Venture classified investments in Norwegian PCs by Norwegian VC firms after enlarging the data sample		901
5	Removing missing organization number	-10	891
6	Removing missing investment year	-392	499
7	Removing all the duplicates	-142	357
8	Removing later rounds of investments	-62	295
9	Removing same company being registered twice	-16	279
10	Removing observations in which the VC firm is not the most specialized among the joint venture partners.	-22	257
	Data sample retrieved from the ACPE database		**257**

3.2.2 Merging Procedure

In this sub-section we will describe the procedure of merging the transaction data from the ACPE database with the data from the SNF database.

11) Merging data from the ACPE database with the SNF database.

After retrieving transaction data from the ACPE database we merged this data with the accounting and company information from the SNF database. Doing this, we used organization number for each PC as the key identifier variable. Merging these two data sources reduced the sample size for two reasons. First, some of the PCs from the ACPE database, identified with a unique organization number, where not found in the SNF database. Second, some of the PCs where, in the SNF database, only registered with accounting data prior to, or after the year of investment, and not in the year of the investment. In total, the sample size was reduced by 41 observations.

Table 3.2.2 illustrates the procedure resulting in the data sample after merging the ACPE database with the SNF database.

Table 3.2.2: Overview of the process constructing the data sample

Step	Description	Effect	Sample size
11	Data sample retrieved from the ACPE database.		253
	Merging data from the ACPE database with the SNF database	-41	212
	Data sample after the merging procedure		**212**

3.2.3 Constructing the Final Data Sample Used in the Analysis

In this sub-section, we will outline how we constructed the final data sample used in the analysis. We provide a summary of the enumerated steps at the end of this sub-section.

12) Removing observations with missing Nace07 code.

The SNF database fared perfectly well providing us with most of the accounting and company information required in our analysis. However, we did experience that 14 of the PCs were registered without their main industry code (NACE07 code) in the year of investment. This information is required in order to calculate the specialization scores. Avoiding losing more observations we did an effort in providing this information. Most of the PCs are also registered with their main industry code derived from the old NACE classification from 2002(NACE02 code). By using a converting table compiled by Statistics Norway (SSB) (Haugen, 2009) we managed to convert the old NACE02 codes to the new NACE07 codes. We contacted SSB in order to make sure that this technique was reliable. Investigating observations in the SNF database, which contained both NACE02 codes and NACE07 codes, we ensured that the converting technique used by SSB was coherent with the converting technique applied by SNF. In some cases, the converting table suggested several NACE07 codes for one unique NACE02 code. In these cases, we found descriptions of the PCs in order to select the appropriate NACE07 code related to the activity in the PC. Among the 14 observations with missing NACE07 codes, we were able to obtain 13 of the codes, reducing the number of lost observations to 1.

13) Removing observations with missing values in year three or five.

The merging process ensured that all the observations were reported with accounting information in the year of investment. As we seek to measure the performance of the PCs in year three and five, we are also dependent on the observation being registered with information in these years. Thus, we made sure that we only were left with observations fulfilling these requirements. Balancing the data sample also ensures that we compare the performance of the same PCs in our analysis.[5] This results in 48 observations being dropped. The main reason for this considerable number of observations is the fact that most of these PC have been invested in after 2010, preventing us from measuring performance in year five.

14) Removing the first and second investment of the VC firm

We argue that we find it too early to determine anything with regards to specialization in a VC firm solely based on the first or the second investment undertaken by a VC firm. The first and second investment in a VC firm does not necessarily reflect the composition of the human capital in the VC firm or their strategy in terms of specialization. Further, we argue that the specialization scores if assigned to these observations could be a result of coincidence due to the low number of previous investments. As we are dealing with a limited number of observations we are aware of the downside of removing observations. However, based on the arguments provided above we conclude that deleting these variables makes the analysis more robust, and exceeds the downside of removing them. However, we would like to pinpoint that the rest of the specialization scores are calculated *before* the first and second investments are removed. Thus, these investments are taken into account when determining the specialization score following the first and second investment. Removing the first and second investment undertaken by VC firms results in 43 observations being removed. Table 3.2.3 depicts the procedure resulting in the final data sample.

[5] This is except from the logit regressions in which some of the observations are not used.

Table 3.2.3: Overview of the process constructing the data sample

Step	Description	Effect	Sample size
	Data sample after the merging procedure		212
12	Removing observations with missing Nace07 codes	-1	211
13	Removing observations with missing values in year three or five	-48	163
14	Removing the first and second investment of the VC firm	-43	120
	Final data sample being used in the analysis		**120**

3.3 Possible Biases

In this section, we present the biases that we consider as the most relevant considering the representativity of our data sample. First, we will focus on the bias that may occur due to PCs disappearing from our data sample during the time period we analyse. This is referred to as a survivorship bias. Second, we will present the bias that may be present due to the selection of our data sample, described as a selection bias. We will discuss how the presence of these biases might influence our analysis, and discuss whether we have sufficient evidence to believe that our analysis is subject to either of the two. Before we start, we would like to emphasize that the selection bias introduced in this part only refers to the bias resulting from the procedure constructing the data sample. The case in which the selection bias results from different VC firm's ability to screen and select promising PCs, or promising PC´s preference regarding different VC firms, is outlined in the methodology part.

3.3.1 Survivorship Bias

The survivorship bias is a concept based on a skewed survival rate in which the companies that went bankrupt, during the time of interest, are left out of the analysis. This causes the results to be skewed in favour of the successful companies (Moen & Riis, 2001).

Related to our situation, a survivorship bias may arise if many poor performing PCs go bankrupt during the time we investigate and disappears from our data sample, leaving us with a data sample being skewed towards better-performing PCs. Further, for a survivorship bias to be present in our data sample, there has to be a significant difference between the number of PCs that disappears, that are backed by a VC firm with a high or low degree of specialization. If for instance, all the PCs with poor performance that disappear are backed by

VC firms with a high degree of specialization this will not be taken into account, causing the results to overstate the effect of specialization on performance in PCs[6].

In order to assess whether our data sample suffers from a survivorship bias we first identified PCs that was included in our data sample in year one but not in year five. We removed all the companies invested in after 2010 so that we only were left with the PCs that had disappeared from the dataset for other reasons than missing information in year five. By doing this we were able to identify 11 PCs. One approach is to assume that all these cases are failed companies that went bankrupt, skewing our final dataset towards successful companies. However, disappearing from the data sample might not always be the case of companies suffering from bankruptcy. It could be that these PCs where promising PCs and have therefore been subject to M&A activity. Thus, in order to draw the right conclusion, we expanded our survivorship analysis to classify three different events. i) Mergers ii) acquisitions and iii) bankruptcy. By looking at the information provided in the SNF database, historic announcements from the PCs provided at regnskapstall.no, and the Zephyr database we were able to classify these events as seven cases of bankruptcy, two mergers and two acquisitions. We also searched through news articles related to the M&A events in order to be able to infer whether these PCs could be considered as promising companies or failures. In the two merger-cases, we were not able to find any information indicating either of the two. Concerning the acquisitions, we found information describing the two companies as highly promising, Nimsoft (Blue, 2010) and MetaMerge (Strøm, 2002).

Further, we investigated the 11 companies in terms of their degree of specialization[7]. This was done in order to learn whether these companies differed in terms of degree of specialization compared to the rest of the dataset. As our specialization score is continuous we investigated whether the PCs could be considered as being backed by a VC firm which is among the 50% most specialized VC firms measured by degree of specialization, i.e., the *mostspecialized* variable equals 1. In the rest of the data sample this yields 50% of the PCs. Doing this we

[6] We exemplify by using the explanatory variable *Spec*. Similar reasoning applies for the other explanatory variables, depending on what explanatory variables we include in the regression models.

[7] This has also been done consdiering the other explanatory variables. The conlusion remains the same.

found that this was the case for only one out of seven PCs that went bankrupt, none of the mergers and both of the acquisitions.

Based on this, it may be tempting to infer that the PCs that went bankrupt are more often backed by the least specialized VC firms, and that PCs being acquired are more often backed by more specialized VC firms. However, as this survivorship analysis is based on a low number of PCs, we cannot infer anything of statistical significance. Thus, it is not possible to decide whether a potential bias overstates or understates the effects concerning the degree of specialization. In addition, the companies that disappear represent less than 10 % of the data sample. Thus, limiting a possible survivorship bias. In total, we conclude that we do not have sufficient evidence to believe that the survivorship bias affects the results presented in the analysis.

3.3.2 Selection Bias

Another bias that may arise from our data sample and affect our results is the selection bias. When collecting data, one risk sample selection bias if observations from the population are left out of the sample on a non-random basis. This can, among other reasons, occur from the data collection procedure. If a non-random selection procedure has been applied when structuring the sample being analysed, the results might suffer from a selection bias, as the sample no longer reflects the population (Berk, 1983).

Applied to our case, the process leading up to the PCs included in our final data sample might introduce a selection bias. This is the case if there are reasons to believe that the procedure applied, results in a sample in which does not reflect the population of Norwegian PCs. If our sample does not reflect the true population of Norwegian PCs we will not be able to generalize the interpretation of our results. If the procedure of excluding PCs is non-random we might both end up with PCs performing better or worse than the population of Norwegian PCs in general. In case of the former this will overstate the effect of VC funding in general on the performance of PCs, and understate the effect in case of the latter.

As in the case of the survivorship bias, the ability to generalize the results will be violated if there is a significant difference between the number of PCs that are left out of the data sample, that are backed by a VC firm with a high or low degree of specialization. However, in difference to when analysing the presence of the survivorship bias, we will to a limited extent be able to tell something about the PCs that are left out of the data due to the lack of information related to these PCs. We will outline this further throughout the discussion.

When considering the ACPE database we have no reasons to believe that the VC transactions included in this database does not reflect the true population of Norwegian VC firms. It is founded on open sources and contains most of the private equity deals in the Nordics. The ACPE is an independent academic research institution, and we believe that constructing this data has not been subjected to favouring any type of particular information. In addition, the database has for long been used when studying private equity deals. Going through some of these studies we find no indication of the author raising any concern related to selection bias when using the ACPE database as a source, e.g. "*Leveraged Buyouts in Norway"* (Bienz, 2016).

The more troublesome part, with regards to selection bias, is the fact that several PCs are left out of our data sample due to the lack of information on the time of investment. In the process of providing this information, we learned that VC firms are in general reluctant to disclose information about both the time of investment and the time of exit. One might reason that they are unwilling to provide this type of information, as it allows evaluations of returns of the investments when knowing the holding period. In the extension of this, one might reason that only information of the investments considered as successful, and yielding satisfying returns, are provided. If this tendency is true in our population sample, it will contain a larger fraction of successful PCs then the true fraction of successful PCs in the population. This will cause our results to be biased, as the effect of VC funding will be overstated. Using sources as Wayback Machine, allowed us to find details of PC investments no longer listed in the portfolio of different VC firms. By this, we managed to include time of investments in PCs irrespectively of outcome of the investment. However, as we managed to retrieve far from all the missing investments years we cannot say that we overcome the possible selection bias arising from PCs being left out due to missing information on time of investment. In order to decide whether the PCs that are left out of the sample statistically differs from each other in terms of being backed by VC firm with different degrees of specialization we need to know the time of the investment of the PC. However, as this information is not provided we are not able to decide this, concerning the PCs that are excluded from the data sample.

Before we arrive at our final data sample we also exclude the first and second investment undertaken by a VC firm. If the companies being dropped results in the final data sample not being representative for the population this may introduce a selection bias. One might reason that it takes time for a VC firm to acquire skills related to both selecting promising PCs with good prospects, and skills that could provide competent guidance and support to the PCs. Thus, one might reason that the first PCs in which the different VC firms invested in performs worse compared to the PCs being invested in when the VC firm has gained more experience. On the other side, one might argue that the first PCs invested in by VC firms receive more attention and support due to the low number of other PCs competing of being prioritized by the VC firm. Based on this we believe that the potential selection bias arising from this step in the sampling process is limited. As described in step 14 in the data sampling process we are not able to determine the degree of specialization in a VC firm based on the first and second investment. Thus, when these PCs are excluded from the data sample we are not able to infer whether they differ significantly from each other in terms of being backed by VC firm with different degrees of specialization.

In total, after having outlined the sources we believe to be the most relevant for a selection bias, we argue that we do not have enough evidence to infer that our data sample is subject to a selection bias. By this, we also imply that we do not have sufficient evidence to conclude on the opposite.

4. Methodology

Our methodology is in large part based on the measures of corporate diversification presented by Caves, Porter and Spence (1980). Gompers et al. (2009) present a measure of industry specialization which is industry experience divided by general experience. In other words, the fraction of previous investments being in the industry in question. We make use of these measures to determine to what degree the portfolios of the VC firms are industry specialized. We are not familiar with others previously making use of the concentric index of related diversification to assess the degree of industry specialization of a VC firm. However, following the reasoning related to the sharing of resources between the VC firm and its PCs, and among PCs under common ownership, we posit that the dynamics within a VC portfolio is similar to the dynamics in a corporation.

This chapter on methodology is structured as follows. We first present the general models, thereafter we will treat the dependent, explanatory and control variables in different sections. We will present strengths and limitations with the different measures and empirical models used in our thesis.

4.1 Regression Models

The models used to identify the value-adding effects of venture capital industry specialization are multiple regression models, logit models and multiple regression models including interaction terms. The use of regression models allows us to study the relationships among variables, and to test if these relationships are of statistical significance. As our data sample is composed of 120 PCs we report statistical significance at 1%, 5% and 10% in the thesis. Due to the low number of observations we find it economically meaningful to interpret results that are within a 10% significance threshold.

4.1.1 General Model

The general model states that the performance of portfolio company i is a function of the industry specialization of the venture capital firm that has invested in the portfolio company.

$$Performance\ indicator_i = \alpha + \beta_1 * Specialization\ measure_j + \beta_2 * X_1 + \ldots\ldots + \beta_{16} * X_{15} + \varepsilon$$

We make use of OLS regressions including controls, X_l, for the most central features thought to influence the performance of portfolio companies besides the VC´s degree of industry specialization.

4.1.2 Logistic Regression

The logistic regression models are the general model making use of binary performance measures, e.g. increased/not increased profits. We make use of the logistic model rather than a regular OLS regression in order to restrict probabilities within the boundaries of zero and one.

$$\Pr(Performance\ indicator_i{=}1 \mid Specialization\ measure_j) = \mathrm{F}(\alpha + \beta_1 * Specialization\ measure_j + \beta_2 * X_1 + \ldots\ldots + \beta_{16} * X_{15} + \varepsilon)$$

The coefficient of the specialization measure variable cannot be interpreted directly. It must be translated using the logistic function.

$$F(\alpha + \beta 1 * Specialization\ measurej\ ) = \frac{1}{1 + e^{-(\alpha + \beta 1 * Specialization\ measurej\ )}}$$

After this transformation, the coefficients are interpreted as the change in the probability that the performance measure equals one.

4.1.3 Regression With Interaction Term

The use of interaction terms makes it possible to study the combined effect of different variables. The interaction term is given as the product of variables thought to have different effects when together as opposed to alone.

$$Performance\ indicator_i = \alpha + \beta_1 * Related\ Specialization\ measure_m + \beta_2 * Industry\ Level\ Specialization\ measure_n + \beta_3 * Related\ Specialization\ measure_m * Industry\ Level\ Specialization\ measure_n + \beta_4 * X_1 + \ldots\ldots + \beta_{18} * X_{15} + \varepsilon$$

If the coefficient of the interaction term is statistically significant there is a combined effect of the variables included in the interaction term. The coefficients of the variables included in the interaction are, as separate variables, interpreted as the effect of the variable when the other variable included in the interaction equals zero. This makes the interpretation somewhat less meaningful when dealing with continuous variables. The effect of a continuous variable when the dummy variable equals one is the sum of the effect when the other variable equals one and the combined effect, i.e. $\beta_1 + \beta_3$.

Having presented the different types of regression models used in the analysis, we now continue to a description and discussion regarding the variables included in our model. We will first present the different performance measures. Thereafter, we turn to the explanatory variables measuring specialization before ending in a discussion regarding the included control variables. At the end of the following parts presenting the dependent, explanatory and control variables, we will present a table displaying a summary of the variables chosen with short explanations.

4.2 Dependent Variables

Company performance can be measured in various ways. Differences in both product and market strategies of firms make it difficult to evaluate all companies using the same performance measures when looking at a relatively short timeframe. The PCs included in our study are mainly ventures raising capital as part of a growth strategy. Whilst some young firms grow organically, others rely heavily on up-front investments in research, marketing or in establishing a market position providing the necessary scale for profitable operations. Given these differences among firms, we argue that there is no perfect single measure for portfolio company performance in the short run. We have chosen five different measures of performance which are both relevant in the assessment of PC performance and has a distribution that makes them usable in regression analyses.

Meaningful ordinary least squares multiple regression analysis depends on four assumptions regarding the variables included in the regression model. First, the error term should have an expected value of zero independent of the value of the explanatory variable. Second, the observations should be i.i.d., i.e. identically and independently distributed. Third, big outliers should be rare, and not resulting from errors in the collection of the data. The fourth and final assumption is that there is no perfect multicollinearity. The second assumption is dealt with in the chapter on data and biases. The first is dealt with by the use of control variables. We will in the following paragraphs discuss the choice of performance measures considering the third and fourth assumption.

Outliers are observations with values that to a large degree differs from what should be expected given the distribution in the sample and the nature of the variable in question. The data sample used in our analyses do have observations of revenues, costs and profits that are extreme compared to the averages in the sample. However, they should not be treated as outliers without taking the nature of our sample into concern. What should be deemed normal when studying PC performance? A particular feature of PCs is that they are extremely risky investments, where the VC funds only expect about two out of ten investments to be profitable. In addition to such a poor success rate in general, there is the hope of investing in the next "big thing" such as Spotify or Snapchat, of which the chances are even smaller. So, which observations of performance should be deemed abnormal? We find it plausible that none of the extreme observations are outliers that should be excluded from the data sample. We have used public accounting data from proff.no and regnskapsdata.no to verify that the extreme values do not result from errors.

Even though the extreme values are not outliers that can be removed, they do have great influence on the regression analysis. In addition to heavily influencing the results of the regression analysis, their inclusion results in a violation of the OLS assumption 1. As the outliers are not evenly distributed across the other variables, being so few, their presence results in skewness, with the expectations of the error term not being zero across all values of the included variables. To overcome this violation, we make use of two different approaches. First, we divide the performance into two groups, resulting in binary dependent variables and the use of logistic models. Second, we use logarithmic transformations when studying continuous variables. The main weakness of this approach of logarithmic transformations is that they discard observations being equal to zero. We overcome this problem by adding the value one to all observations of performance. We make use of growth rates defined as the logarithm of for example revenues in the final year over revenues in the base year. This measure of growth rates, depending on logarithmic transformations as described in the previous paragraph, do not have a problem concerning extreme values.

The fourth OLS assumption is that there is no perfect multicollinearity between the variables included in the model. By the use of growth rates rather than including lagged observations we overcome the multicollinearity problem. One of the alternatives to this approach would be to compare levels in the final year and control for the level of the variable in the investment year. This would, however most certainly result in a problem regarding multicollinearity. Other approaches to the use of panel data are fixed effects regressions and differences in differences estimation. We make use of a data sample containing few observations, and the additional requirements related to the data sample regarding the use of differences in differences estimation reduces the data sample to 84 observations. We find this too small of a sample to estimate the effects of VC firm industry specialization.

We present analysis of three different event windows. The first event window is defined by the period from the time of investment (year one) to year five. This is used to test the effects of VC firm industry specialization, on PC performance, from VC entry until the fifth year after the investment. This period is chosen due to the nature of venture capitalists being invested in a portfolio company for four to six years before exiting the venture. There might, however, be significant differences in the effects on PC performance within the mentioned event window. We have for this reason included two sub-periods of the five-year window.

The first of the two sub-periods of the event window ranges from the investment year (year one) until the third year, allowing us to see immediate effects of industry specialized VC´s on performance. It is plausible that some of the effects related to resource availability, signalling of quality to potential partners and access to the VC´s network materialize quite short time after the VC entry. Assuming that we are able to control for selection effects on performance, the presence of differing effects of specialization between the first sub-period and the entire period would indicate that the value-adding effects differ in nature between the event windows.

The second sub-period of the event window ranges from year three to year five. The effects dependent on changes in management, strategy or that by other means requiring more time to influence the operations of the PC, will not materialize in the form of changes in performance until some years after the VC entry. It is for this reason interesting to study if there are differences regarding the effects of the VC´s degree of industry specialization between the sub-periods.

The following paragraphs will present the five different performance measures included in our models. First, we present the two binary measures and the rationale for making use of binary performance measures. Thereafter, we present the continuous measures and explain why we include both measures in the analysis.

We define the two following performance measures as the ability of a portfolio company to increase their profits or revenues in the period in question. This measure is not subject to concerns relating to extreme values, and may therefore be more robust than the continuous variables used elsewhere in the analysis. There are multiple firms in our sample experiencing large declines and increases relative to the other firms. A weakness with the use of binary performance measures is that they do not capture the variance among companies within the groups. Continuous variables are able to make use of differences not included in binary measures.

A. Increased Profits

In the long run, a company's ability to generate profits is the gold standard for measuring performance. If the company creates value, this value creation will be awarded by the company generating more revenue than costs, i.e. a profit. The increases in profits range from being strongly negative to strongly positive. Our measure *Increased Profits* is a binary variable that equals one if the portfolio has experienced a positive increase from the beginning to the end of the period, and zero otherwise. The share of companies being successful in increasing their profits equals approximately 50% of the portfolio companies in all periods.

There are concerns related to the use of profits as a standalone measure of the performance of young firms. The companies receiving venture capital differ from most other firms along several dimensions. First and foremost, they are risky ventures that are thought to have large growth potential if successful. Due to the uncertainty and risk associated with investing in new firms, the successful ventures must generate large enough profits to compensate the owners. To do this, the portfolio companies need to grow fast. Firms do have different growth strategies, where a large fraction involves running the business on deficits in the first years after VC entry in order to improve the product, or to build a market position. Considering these aspects with the VC business one may argue that profits alone are not sufficient to determine whether or not a portfolio is achieving high performance.

The particularities concerning companies receiving venture capital are in addition to affecting profits as a performance measure, affecting the choice not to use a variety of other performance measures related to profits. Profit margins, return on investment, return on equity and economic value added are all measures that make use of multiple accounting measures in order to provide meaningful performance measures allowing for comparison across businesses. We argue that these measures are even less suited than profits as performance measures in our analysis because there are, in addition to the weaknesses related to profits, weaknesses related to the other components of these measures. As one example two firms with equal profits that differ in the amount of equity capital, will get different returns on equity (ROE). Normally, one reckons higher ROE to outperform lower ROE. In ventures, the interpretations might be that a company having more equity has received more venture capital than another company, thus being the company thought to have the best prospects.

Nevertheless, assuming that the probability of surviving in the competition, and of following a strategy resulting in planned deficits, is equal for specialized and diversified venture capital firms, their ability to add value may be measured by whether or not one has been able to increase profits.

B. Increased Revenues

Increased Revenues might be a more appropriate measure of performance, than increase in profits, for growth firms following different expansion strategies. The measure is defined as follows,

Increased revenue$_{1\text{-}5}$ = 1 if the revenues in year 5 are the double of revenues in year 1

Increased revenue$_{1\text{-}3}$ = 1 if the revenues in year 3 are 40% higher than in year 1

Increased revenue$_{3\text{-}5}$ = 1 if the revenues in year 5 are 30% higher than in year 3

We have divided the firms into two groups such that about the 50% of the firms that experience the highest increase in revenue from the base to final year are identified with the binary variable taking the value 1. We make use of these classifications due to the ease of interpretation from the use of a 100%, 40% and 30% percent increases.

In the following, all growth variables are calculated in the same way, and all binary variables regarding increases are calculated equally. We have defined growth as the logarithm of the fraction of the clean dependent variable after a period over the variable before the period, formally:

$$Growth = \log\left(\frac{Measure_{End} + 1}{Measure_{Beginning} + 1}\right) = \log(Measure_{End} + 1\,) - \log\,(Measure_{Beginning} + 1)$$

C. Revenue Growth

Revenue Growth is an important measure of PC performance because it measures the growth in economic activity between the firm and their customers. We assume that most PCs will launch a product and generate revenue at least during the five years following a VC entry. In such a case, the growth in revenues will measure the firm´s ability to sell their products and/or services. By using the log transformation on growth rates we reduce the problem related to extreme observations of growth rates.

There are weaknesses related to revenue growth as a performance measure. Some PCs may have a strategy that does not generate revenues even if its considered as successful. This is true for both companies that depend on exhaustive research and development before launch, and for companies providing platform services where the user base is an important part of the product/service. Applications such as Snapchat and Kahoot did not generate revenues the first years of its existence, while few argues that they have a poor performance. Another weakness of revenue growth as a measure is that it does not account for the costs related to the generation of the revenue stream. A growth strategy that generates a higher growth in costs than revenues in the long run is doomed to fail.

D. Payroll Growth

We include *payroll growth* as a measure of performance for the PCs due to its ability to measure economic activity within the firm without being related to the product market and the weaknesses related to measures such as revenue growth as described in the last section. An alternative measure to payroll is the number of employees. We choose payroll because it enables us to differentiate between highly compensated and lower compensated employees. One may argue that opening for differences related to the cost of labour enables the measure to better capture the level of investment in research and development in the firm. This argument depends on the assumption that labour first and foremost contributes to research and development in newly ventured firms.

There are several weaknesses with payroll growth as a measure of PC performance. First and foremost, it only measures the costs related to the firm’s activity, ignoring the relation to income. Secondly, it ignores that labour compensation exists in different forms, such as ownership stakes, stock options and bonuses, in addition to salary. These untraditional types of labour compensation are common among young firms unable to attract talent with traditional compensation such as salaries.

E. Productivity Growth

Productivity Growth measures the growth in the fraction of revenue to payroll, i.e. the firm´s ability to increase revenue generated per labour cost. This is a commonly used measure of labour productivity. Even though it is a very simple measure of productivity, it is nevertheless able to identify the relation between revenue and labour cost. We prefer this measure to other productivity measures due to its simplicity. In addition, opposed to earlier mentioned measures of performance, this one considers the relationship between revenue and costs.

However, this measure only accounts for the labour costs in the form of salaries and ignores other costs such as rent, financial costs, management and juridical counsel etc. Young firms are likely to use other compensation forms than salary to attract talents. They are also likely to use a large fraction of their income on other costs as long as there is little revenue generation compared to the costs associated with rent and other fixed costs. Table 4.2.1 displays a summary of the depended variables chosen with short explanations.

Table 4.2.1: Summary of the dependent variables

Dependent Variables	**Explanation**
Increased Profits	Dummy variable equal to 1 if the PC in question experience increased profits during a given time period.
Increased Revenues	Dummy variable equal to 1 if the PC manages to increase their revenues with 100 %, 40% or 30% from year one to five, one to three or three to five respectively.
Revenue Growth	Variable equal to the change in the logarithm of revenues +1. Formally, the variable is calculated as $\log(totinn_t+1)-\log(totinn_{t-j}+1)$, in which j={4,2}.
Payroll Growth	Variable equal to the change in the logarithm of payroll expenses +1. Formally, the variable is calculated as $\log(lonnsos_t+1)-\log(lonnsos_{t-j}+1)$, in which j={4,2}.
Productivity Growth	Variable equal to the change in the logarithm of productivity +1. Formally, the variable is calculated as log(productivity+1)-log(productivity+1), in which j={4,2} and Productivity= (Revenues/Payroll).

4.3 Explanatory Variables

Depending on different definitions of industry specialization one may create various measures of industry specialization. We make use of measures that we have divided into two groups; related specialization and industry level specialization. Our measures of related industry specialization are based on the concentric index for corporate diversification presented by Caves, Porter and Spence (1980). The measures of industry level specialization are based on the specialization measure used by Gompers et al. (2009). We will first present the measures of related specialization before presenting the measures of industry level specialization.

4.3.1 Measures of Related Specialization

We use measures of related specialization to assess the degree of industry specialization of a VC firm making use of methodology from measures of related diversification. In corporate strategy, questions regarding the existence and performance of conglomerates of related and unrelated firms have led to the development and use of a variety of measures of industry diversification. A measure for corporate diversification making use of the hierarchy of industry levels is the concentric index (Caves, Porter, & Spence, 1980). The index makes use of the the hierarchy existing in the SIC code system. It acknowledges differences between industry levels when assessing a diversification score. It accounts for this by assigning different scores dependent on the industry level in which the firms being compared differ in terms of industry categorization. As an example, it will assign a higher diversification score to a conglomerate in which the companies operate in different sectors, than to a conglomerate where all the companies operates in different industry sections. The final score depends on the relations among all the individual parts of the conglomerate, taking into account the different distances between industry levels. It is a measure of *related* diversification. The formal description of the concentric index is as follows:

$$DC = \sum_{i=1}^{N} P_{ki} * \sum_{k=1}^{N} P_{kl} * d_{il}$$

Where,

P_{ki} is the percentage of sales for firm k in industry *i,*

P_{kl} is the percentage of sales for firm k in industry *l,*

$d_{il} = 0$ where *i* and *l* belongs to the same 3-digit SIC category,

$d_{il} = 1$ where i and l belong to the same 2-digit SIC group but different 3-digit SIC groups, $d_{il} = 2$ where i and l are in different 2-digit SIC codes.

d_{il} is a variable weighting factor, allowing for giving different importance to differences, according to whether it is a difference in industry sections, industry divisions or industry groups.

Caves et al. (1980) developed The Concentric index for use in the US, basing it on the SIC code system. Our measures of related specialization are based on the NACE system, which is the "statistical classification of economic activities in the European Community" (Eurostat, 2008). The logic of the NACE system is quite similar to the SIC system. It has quite broad industry sections (NHOs), functioning as umbrellas for several industry sections (the first three digits of the NACE codes), that in turn functions as umbrellas for a variety of industry groups(the first four digits of the NACE codes) (Statistics Norway, 2017). The

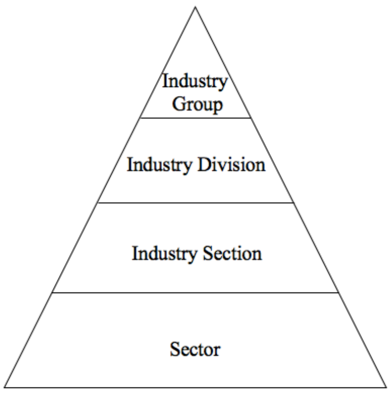


Figure 4.3.1: *Hierarchy of industry levels from broad to narrow industry categorizations.*

In addition to the use of the industry levels described in the NACE codes, we have added the sector classifications included in the SNF database as an overarching industry level for the industry sections. The structure is illustrated in figure 4.3.1.

The concentric index relies on some strong assumptions. It assumes that the distances between all industry categories at the same industry level are equal. It also assumes that the level differences among all hierarchies of industry levels are equal.

We make use of a total of six measures of specialization derived from the methodology of related diversification. These can be divided into two groups; portfolio relatedness and degree of related specialization.

Sharma (1998) presents the measure *product relatedness* building on the *Weighted Index* presented by Caves et al (1980). It is constructed in such a way that it measures the relatedness between an entrant business and the rest of the businesses of the parent firm by making use of the variable weighting factor based on the SIC system. It is a modified version of the concentric index. The formal description is as follows:

$$\text{Product Relatedness} = \sum \mathrm{P_{kl}} * \mathrm{d_{il}}$$

where,

P is the percentage of firm k´s sales that are in the industry l
d_{il} is the weight whose value depends upon the distance between the entered industry *i* and the other industries l in which the parent has operations.

Our measure *Match,* measures portfolio relatedness. It is based on the *Product Relatedness* measure proposed by Sharma (1998). The formal description of the *Match* measure is as follows:

$$Match = \sum_{l} P_i * d_{il}$$

where,

P_i is the fraction of the portfolio invested in the four-digit NACE code i,

d_{il} *= 0 if the portfolio company i is in a different sector than the new entrant's industry l.*

d_{il} *= 1 if the new company in the portfolio is in the same sector as company(ies) l.*

d_{il} *= 3 if the new company in the portfolio is in the same NHO/industry section as company(ies) l.*

d_{il} *= 6 if the new company in the portfolio is in the same 3-digit NACE code/industry division as company(ies) l.*

d_{il} *= 10 if the new company in the portfolio is in the same 4-digit NACE code/industry division as company(ies) l.*

Match is a measure of the portfolio relatedness between the PC receiving venture capital funding and all the previous investments undertaken by the VC firm. The PC's portfolio relatedness with the existing portfolio is defined by to what degree the VC firm has a lot of experience with the specific industry of the investment. This measure makes use of the variable weighting factor based on NACE codes to assess the distance between the new company to the portfolio and all previous investments. Figure 4.3.2 illustrates the portfolio relatedness between a new PC and the existing portfolio.

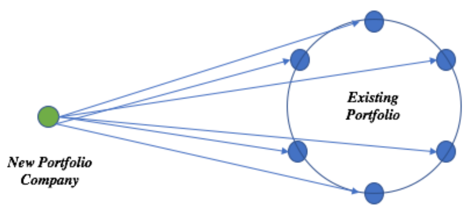


Figure 4.3.2: *Match captures the portfolio relatedness between an existing portfolio and the new PC.*

We have inflated the level differences of the value weighting factor d_{ij}. The concentric index makes use of level differences of one and two, i.e. the difference between two firms in different industry sections is twice the size of the difference between two firms in different industry divisions whilst in the same industry section. In addition to having turned the scale upside down, letting it increase with the degree of industry specialization, we make use of *d´s* ranging from zero to ten. The choice of this range relates to the decision to include the total of four industry levels, rather than using the original two. The concentric index was created to measure corporate diversification. We base our choice to include four industry levels on the assumption that the effects of specialization are present at a lower level of industry specialization when studying effects of ownership than of effects concerning corporate diversification. Moreover, we want the score to reflect the differences of the different industry levels. Sectors are a very broad categorization, whilst industry groups are very small compared to sectors. We assume that there are effects of specialization at the sector level and that these are small compared to the effects of specialization at more precise industry level classifications. The choice of scores of 0, 1, 3, 6 and 10 allows for the more precise categories to always have an increasing impact on the degree of related specialization.

We include *match* in three different forms in our models. First, we make use of *Match* as is. Second, we include *Match squared* so that we may capture non-linear effects of this form of related specialization on portfolio performance. Lastly, we include a binary measure named *Bestmatch* taking the value one if the investment in question is one of the investments having the 50% highest Match scores. The binary measure is included to test a more robust measure, i.e. a measure not dependent on the weights used in the variable weighting factor and less dependent on the NACE assumptions regarding distances between different industries.

In addition to *match* as a measure of related specialization we make use of the measure *Related Specialization.* It is based on the concentric index, making use of the connections among all previous investments in addition to all the connections between the new entrant and the previous investments when calculating the degree of specialization of the VC firm for the investment in question. This relationship is illustrated in figure 4.3.3.

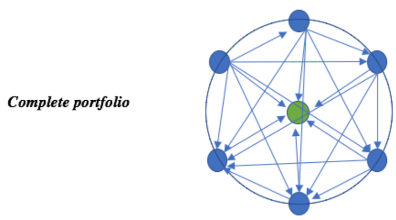


Figure 4.3.3: *Related Specialization captures the overall relatedness among all firms in a portfolio.*

The degree of related specialization does in addition to measure the distance of the new entrant to the existing portfolio measure the degree of specialization in the existing portfolio. Thus, related specialization is a measure of portfolio specialization. One plausible outcome is that the new entrant to the portfolio is completely unrelated to the existing portfolio, $d_{ij}=0$ for all connections, whilst the degree of related specialization is high. This is the outcome of a VC being specialized in one industry invest in an unrelated industry. That instance would generate a *Match* score equal to zero, and a strong positive degree of *Related Specialization.* The formal description of the *Related Specialization* measure is as follows,

$$Related\ Specialization = \frac{\sum_{m=1}^{M} \sum_{l}^{L} P_{mi} * d_{il}}{\frac{1}{2} * M * (M-1)} = \frac{\sum_{m=1}^{M} Match * (M-1)}{\frac{1}{2} * M * (M-1)}$$

where,

P_{mi} is the fraction of the portfolio invested in the four-digit NACE code i in the m^{th} investment of the venture capital firm,

M is the number of companies within the portfolio, i.e. the number of previous investments undertaken by the VC firm,

$\frac{1}{2} * M * (M - 1)$ is the number of connections among companies i within a portfolio of M companies. We divide the sum of the variable weighting factors d on the number of connections in order to normalize the score across all different portfolio sizes.

d_{il} *= 0 if the portfolio company i is in a different sector than the new entrant's industry l.*

d_{il} *= 1 if the new company in the portfolio is in the same sector as company(ies) l.*

d_{il} *= 3 if the new company in the portfolio is in the same NHO/industry section as company(ies) l.*

d_{il} *= 6 if the new company in the portfolio is in the same 3-digit NACE code/industry division as company(ies) l.*

d_{il} *= 10 if the new company in the portfolio is in the same 4-digit NACE code/industry division as company(ies) l.*

We include *related specialization* in three different forms in our models. First, we make use of *related specialization, Spec***,** as is. Second, we include *Spec squared* so that we may capture non-linear effects of this form of related specialization on portfolio performance. Lastly, we include a binary measure named *Mostspecialized* taking the value one if the investment in question is one of the investments having the 50% highest *Spec* scores. The binary measure is included to test a more robust measure, i.e. a measure not dependent on the weights used in the variable weighting factor and less dependent on the NACE assumptions regarding distances between different industries. Table 4.3.4 displays a summary of the Related Specialization Measures with short explanations.

Table 4.3.4: Summary of the Related Specialization Measures

Related Specialization Measures	Explanation
Spec	Variable measuring the related degree of specialization of a VC firm. The score ranges from 0 to 10, where 10 and 0 are the highest and lowest degree of related specialization respectively.
Spec^2	Variable equal to the squared value of the spec variable.
Mostspecialized	Dummy variable equal to 1 if the PC is backed by a VC firm which is among the 50 % most specialized VC firms measured by related degree of specialization, and zero otherwise.
Match	Variable measuring the portfolio relatedness between the new entrant and the existing portfolio of companies. The score ranges from 0 to 10 where 10 is a complete match, and 0 is total difference between the new PC and the PCs in the existing portfolio.
Match^2	Variable equal to the squared value of the match variable.
Bestmatch	Dummy variable equal to 1 if the PC is considered as among the 50 % best matches in the data sample, and 0 otherwise.

4.3.1.1 How to Construct the Related Specialization Measures in Stata

In order to calculate the variables based on related specialization we have constructed a range of variables. We have built a syntax in Stata which goes through all previous investments undertaken by the VC firm and assigns points to the same variables if the criteria are met. These scores are in turn used for the computation of the measures for related specialization. The process resulting in the Related Specialization Measures are displayed in table 4.3.5

Table 4.3.5: Overview of the process resulting in the Related Specialization Measures.

Variable	**Explanation**
Same Sector	Score in intervals of 1. For each previous investment by the VC in the same sector one gets a score of 1. For all previous investments in another sector one gets 0. Cumulates over the number of investments undertaken by the VC firm.
Same NHO	Score in intervals of 2. For each previous investment by the VC in the same NHO one gets a score of 2, for all previous investments another NHO one gets 0. Cumulates over the number of investments undertaken by the VC firm.
Same 3-digits	Score in intervals of 3. For each previous investment by the VC in the same first three digit of the NACE07-code, one gets a score of 3, for all previous investments in another3_digit NACE one gets 0. Cumulates over the number of investments undertaken by the VC.
Same 4-digits	Score in intervals of 4. For each previous investment by the VC in the same four first digits of the NACE-code one gets a score of 4, for all previous investments in another 4_digit NACE one gets 0. Cumulates over the number of investments undertaken by the VC.
Same	Is the sum of *Same_sector*, *Same_NHO* + *Same_3digits* + *Same_4digits*.
Nr investment VC	Variable measuring the number of investments by a VC firm at the time of the current investment.
Nr Connections VC	The number of connections between PCs within a portfolio at the time of the current investment. This number is calculated as a triangular number sequence, i.e. #connections=0,5*Nr Investment VC*(Nr Investment VC - 1)
Match	Is the variable "Same" divided by the variable "Nr Investment VC"
Related Specialization	Is the variable "Same" divided by "Nr Connections VC".

4.3.2 Measures of Industry Level Specialization

The other category of industry specialization measures are measures of industry level specialization. These measures depend on similarities across only one industry level at the time. The measures of *related specialization* depend on quite strong assumptions regarding the NACE code hierarchy of industry levels and at what industry levels specialization influence performance. The measures of *industry level specialization* are simpler measures of specialization, ignoring if companies in different industry sections are part of the same sector when determining their industry specialization. The simplicity of the measure removes the need for assumptions regarding the potential effects of specialization.

The measures of industry level specialization are based on the specialization measure used by Gompers et al. (2009). They define their variable *Specialization* as follows,

$$Specialization = \frac{industry\ experience}{general\ experience}$$

where industry experience is the number of investments undertaken by the venture capital firm in an industry, and general experience is the total number of investments undertaken by the venture capital firm. Building on the *Specialization* measure of Gompers et al. (2009), we construct six different binary measures of industry level specialization.

Two of the main assumptions concerning the related specialization measures is that it is a stronger effect of being specialized at more precise industry categorizations and that this effect increases with the level of specialization. Making use of measures of industry level specialization we can study if there are differences concerning at what level one is specialized. We do this by making use of measures sensitive only to one industry level. The measure also allows us to study if there is a critical mass, defined as the fraction of previous investments in the same industry categorization, needed to reap the benefits of specialization. We do this by testing the effect of different binary variables depending on the fraction of previous investments in the same industry.

The names of the variables measuring industry level specialization are *Preferred"industry level""fraction"* of previous investments in same industry", e.g. *Preferred NHO40. Preferred NHO40* is a binary variable taking the value one if more than 40% of previous investments are in the same industry section(NHO) as the PC in question, and zero otherwise.

Due to data availability we are not able to test all configurations of industry level and critical masses. There are too few observations of portfolio companies backed by VC´s specialized in industry divisions and industry groups to assume a normal distribution of their performance. However, we are able to test if sector and industry section specialization with different critical masses have differing effects, if any, on portfolio performance. Table 4.3.6 provides a summary of all the Industry Level Specialization Measures.

Table 4.3.6: Summary of the Industry Level Specialization Measures

Industry level Specialization Measures	**Explanation**
Preferred Sector50	Dummy variable equal to 1 if a PC operating in $sector_i$ is backed by a VC firm with 50 % or more of previous investments in $sector_i$, and 0 otherwise.
Preferred NHO50	Dummy variable equal to 1 if a PC operating in industry $section_i$ is backed by a VC firm with 50 % or more of previous investments in industry $section_i$, and 0 otherwise.
Preferred NHO40	Dummy variable equal to 1 if a PC operating in industry $section_i$ is backed by a VC firm with 40 % or more of previous investments in industry $section_i$,and 0 otherwise.
Preferred NHO30	Dummy variable equal to 1 if a PC operating in industry $section_i$ is backed by a VC firm with 30 % or more of previous investments in industry $section_i$,and 0 otherwise.

4.4 Control Variables

We include a variety of control variables in our model to accurately estimate the effect of VC specialization on portfolio company performance. The performance of the portfolio companies depends on observable and unobservable characteristics of both the portfolio companies and the venture capitalists. We include control variables for features that may vary between the groups of portfolio companies that are backed by the most and least specialized venture capital firms. We control for these features such that the performance differences among the portfolio companies reflect the differences in the degree of specialization among the venture capital firms. We thus control for both features of the portfolio companies and the venture capital firms. In addition, we control for selection effects.

4.4.1 Controls Related to VC firm Characteristics - Joint Ventures and Number of Investments

In an optimal world for our study, the only characteristic differing among the venture capital firms influencing the performance of PCs should be their degree of specialization. There are, however, characteristics of venture capital firms other than their degree of industry specialization that influence the performance of their PCs.

Brander, Amit and Antweiler (2002) studies the relationship between syndicated venture investments and portfolio performance measured as the annualized return on investment in the portfolio company. Syndicated investments refer to the co-investment activity of two or more VC firms taking part in a joint venture investing in a portfolio company. They find that syndicated investments yield higher annualized returns than standalone investments. It might be that the degree of industry specialization correlates with both the likelihood to take part in joint ventures and PC performance, thus creating an omitted variable bias. We include the binary variable Joint Venture to control for the effects on PC performance related to joint ventures.

We control for the number of investments undertaken by the VC firm. The number of previous investments is a measure related to the experience of the venture capital firm. Gompers et al. (2009) names this measure “general experience”. Venture capitalist experience may affect PC performance through various channels. First, experienced venture capitalists are likely to have accumulated knowledge and skills related to the role as venture capitalists. Secondly, the network centrality (Hochberg, Ljungqvist, & Lu, 2007) of a VC firm is likely to increase over time. Lastly, a VC firm involved in previous successes are likely to have a positive signalling effect (Spence, 1973) for the PC. Experience on the level of each venture capitalist would have been a more detailed measure, however we find VC firm experience measured in terms of number of previous investments to be a suitable proxy.

4.4.2 Controls Related to PC Characteristics – Sector Dummies

We study the performance of Norwegian PCs from a broad range of industries. The performance of the PCs will depend on the development in the sectors in which they are part, e.g. a venture specialising in offshore technology for the oil and gas sector will be more affected by changes in the oil-price than a company in the communications industry. It is likely that we observe differences in performance among the PCs included in our data sample due to differences in performance among sectors and not between specialists and generalists. We include sector dummies to control for the difference in performance resulting from sector specific conditions. There are eight different sectors defined in the database, these are "Agriculture", "Offshore & Shipping", "Manufacturing", "Telecom, IT & Tech", "Electricity", "Wholesale & Retail", "Finance" and "Other services". The baseline sector is Agriculture. These categories are quite broad, allowing for a large degree of variance within the groups. However, we find it likely that the performance of the PCs to some degree is driven by the development in the sector. The choice to control for industry differences at the sector level depends on the sample size of 120 observations, which limits the possibilities related to controlling for differences between entities. Controlling for sectors reduce the risk of the results being influenced by industry specific changes in performance not related to the VC´s degree of specialization.

4.4.3 Controls Related to Time Fixed Effects/Economic Conditions - Financial Bust and Financial Bust Performance

Another factor thought to influence PC performance unrelated to the degree of specialization of the VC firm is the effects of business cycles. Business cycles includes the economic phenomena booms and busts. Booms are periods with high growth in gross domestic product (GDP), and busts are periods with weak or negative growth in GDP. The business cycle affect ventures in at least two ways.

First, high asset valuations and optimism regarding the future increases the likelihood of Venture Capital firms being able to attract capital to fund their funds. This might lead to more venture capital reaching the venture market during booms than in normal times. If the number of profitable business cases is the same over the business cycle such an increase in venture investments would imply that poorer business cases is financed in booms than in normal times or busts. Speaking against this reasoning is the traditional investment horizon of venture capital funds of eight to twelve years, enabling venture capitalists to await better times. The other side to this argument is that there is less capital available for venture capital funds during busts, possibly resulting in VC´s investing in more promising firms than they would otherwise. We include dummy variables taking the value one if the VC entry takes place during a business cycle bust. The rationale to include this variable is that there is likely that these periods are different from “normal” times. Secondly, the business cycle affects supply and demand in both product and factor markets. To account for this, we include a dummy variable equal to one if performance in the PC is measured during the financial crisis, i.e. in 2008, 2009 or 2010.

The dummies included identifying economic busts effect on the venture and product market are used as an alternative to include time fixed effects in our models. This is not optimal, however we find that the combination of making use of these dummies and the assumption of specialized ownership effects being constant over time favours this solution to other solutions not bound by the sample size.

4.4.4 Controls for Selection Bias – Patents Year 1, Years Since Foundation and Years Since Foundation Squared

In the theory chapter, we discussed how VC firms may benefit from industry specialization along two dimensions. First, there are potential benefits related to their superior information availability and ability to draw meaningful conclusions from that information. The superior performance of the portfolio companies backed by specialized VC firms may thus be a result of these VC´s ability to better predict which ventures that will be successful than less specialized VC´s. Secondly, there are multiple potential value adding activities that may be better executed by specialized VC´s. These value adding activities relates to governance, access to business partners through the VC´s networks and the VC´s ability to pool resources across the PCs under common ownership (Lien, 2017). We want to control for the selection effect to study the potential effect of the value adding activities.

The literature includes various attempts to control for selection effects in a VC setting. Bertoni, Colombo and Grilli (2011) make use of dynamic panel-data models to control for selection effects and find that the empirical findings strongly support that VC investments positively influence firm growth. Gompers et. al (2009) includes the following citation in the conclusion of their paper “Specialization and success”, “*It is difficult to determine whether the superior performance of specialists is driven by their ability to better select investments or whether* *specialists are also better able to add value to those investments."* Baum and Silverman (2004) make use of alliance, intellectual and human capital as three winning characteristics of start-ups. They find that often VC firms invest in start-ups having higher levels of these categories of capital, and that these effects performance. However, there is also a positive effect from VC firms on the performance of start-ups additional to this effect. They conclude that there is support for the views of VC firms both as "scout and coach", i.e. that they both pick winners and contribute to further strengthen their performance. Due to restraints regarding the size of our data sample we are not able to make use of the approach presented by Bertoni et al. (2011).

We control for selection effects based on the approach of Baum and Silverman (2004). As we do not have access to data measuring the levels of alliance, intellectual and human capital of the portfolio companies in our dataset we make use of proxies. The proxies found to capture the effects of these forms of capital are; i) value of patents in the PC in the investment year, ii) the years from the founding of the PC to the year of investment and iii) the years from the founding of the PC to the year of investment squared. The value of patents in the investment year are included to proxy the intellectual capital of the portfolio companies. The variable patents includes permits, patents, licences, trademarks, contract rights and copyright (Berner, Mjøs, & Olving, 2016). The years from foundation to investment, and the years from foundation to investment squared are included to proxy for alliance and human capital.

We argue that the years from the founding of the PC to the year of investment is a viable proxy for alliance and human capital of the PCs due to how it naturally coincides with the factors we want to control for. Common for both human and alliance capital is that they accumulate over time. Thus, ventures will gain more and more of these types of capital over their lifetime. However, the ventures may also acquire these types of capital through their choice of employees. Business ventures with high levels of alliance and human capital are likely to exist in two forms, either in the form of the ones established by teams of experienced entrepreneurs with high levels of these forms of capital, or in the form of ventures that have survived over a quite long period, without professional equity funding, accumulating these forms of capital over time. Following this reasoning, firms with high levels of alliance and human capital will receive venture capital at either a short or a long time after the establishment of the venture if the VC´s are able to pick winners. We control for both these instances by controlling for both the clean and squared of the time form establishment to investment.

A potential threat to these control variables is our missing ability to observe the price mechanism in the market for corporate control regarding ventures. On the one side of the market there are VC firms wanting to invest in the ventures showing the greatest potential. On the other side there are entrepreneurs trying to attract investors that are able to provide the resources the venture lacks in order to grow. It is likely that the most important of these resources is capital. However, from the above deliberated theories, it is likely that the entrepreneurs value additional resources as well. If this is the case, the entrepreneur will not be indifferent to which investors gain control over the venture. In this setting, even a rational, profit maximizing entrepreneur can be better off not accepting the highest bid on the venture. This leads to a simultaneity problem where both investor and investee has a say to both when, and at what price ventures are partially sold, where the outside observer only observes the final market solution. A potential outcome in this market is that entrepreneurs turn down offers at higher valuations from venture capitalists thought to be poor at value adding activities in favour of lower valuations from venture capitalists thought to be better at the value adding activities. This will in turn lead to uncertainty regarding our use of the companies age at investment year as a control for the selection bias. If venture capitalists being superior at identifying promising investment opportunities are not able to turn this insight into profitable investments, the company age in the investment year does not measure the quality of the portfolio company.

Making use of the years from the founding of the PC to the year of investment, as a proxy for alliance and human capital in the PC in the investment year, relies on one of the following assumptions. The first of which is that entrepreneurs are exposed to a so large degree of uncertainty regarding the future of their ventures that the expected returns to their efforts are close to zero. In such a case, any reasonable bid on the company in monetary terms will be extremely large compared to the estimated value of the firm to the entrepreneur. Thus, the chance of the entrepreneur accepting the bid is close to 100%. Another assumption that will make entrepreneurs accept any reasonable bid for their venture is that the entrepreneur is driven by the will to create new ventures. If the creation of new ventures is valued more by the entrepreneur than taking part in growing ventures into mature companies, he/she will accept reasonable bids in monetary terms such that he/she can move on to new projects.

Our effort to control for selection bias in order to identify the effect of the value adding activities of venture capital firms is based on strong assumptions and simplifications related to the complexity of the venture capital industry. Baum and Silverman (2004) finds that alliance, intellectual and human capital of the portfolio company at the time of investment has the ability to predict future performance of portfolio companies. We make use of i) the value of patents in the PC in year 1, ii) the years since foundation in the investment year and iii) the years since foundation in the investment year squared, as proxies for these types of capital. We find it plausible that the controls included in our models are able to capture some of the effects on performance related to the selection of portfolio companies. However, including measures of alliance, intellectual and human capital that measures these forms of capital in a more direct manner would further improve our model. Table 4.4.1 provides a summary of all the control variables.

Table 4.4.1: Summary of the Control variables.

Control variables	**Explanation**
Joint Ventures	Dummy variable equal to 1 if the portfolio company is backed by two or more VC firms, and zero otherwise.
Nr. Investment VC	Variable measuring the number of investments by a VC firm at the time of the current investment.
Years Since Foundation	Variable measuring numbers of years between year of foundation of the PC and year of investment.
Years Since Foundation^2	Variable equal to the squared value of years since foundation.
Patents Year 1	Variable measuring the value of patents in the portfolio company in the year of investment (year 1).
Financial Bust	Dummy variable equal to 1 if the PC received first round funding during the financial crisis i.e. in 2008, 2009 or 2010, and zero otherwise.
Financial Bust Performance	Dummy variable equal to 1 if performance in the PC is measured during the financial crisis, i.e. in 2008, 2009 or 2010, and zero otherwise.
Sector	Dummy variable equal to 1 if the PC operates in sectori, and zero otherwise. i={Offshore/Shipping, transport, telecom/It/tech, Electricity, Wholesale/retail, finance or Other services}

5. Analysis

In this chapter, we present the results of our analysis. We start by providing descriptive statistics of the data used in our analysis. Seeking to explore how different aspects of industry specialization in a VC firm affect performance in PCs, we divide our analysis into three parts. Each part address one research question, and answers this by analysing the effect of industry specialization on the five different performance measures. As we aim to examine the timing of these effects, we apply the models on three different time periods. The first represents the entire period, that is, from the time of investment (year one) to year five. The two other periods represent sub-periods, in which the former represents year one to year three, and the latter, the period from year three to year five. When analysing the entire period, we provide full regression outputs. For the sub-periods we provide compressed outputs in which the variables included are limited to the explanatory variables. We present regression outputs throughout the analysis. When analysing the models, the main focus will be on reporting the results of interest. At the end of each part, we will answer the research question, and discuss our findings.

5.1 Descriptive Statistics

Table 5.1.1 presents summary statistics for all variables included in our models. The dependent variables, i.e. the performance measures, differ for the three time periods and are all included in the summary. The explanatory variables, i.e. the specialization measures, and control variables are equal for all time periods.

The performance measures and the specialization measures all relate to phenomena that are likely to affect one another. A PC with high revenues are likely to have high payroll expenses, and a venture capital firm with a high degree of related industry specialization is more likely than less specialized firms to invest in a PC within its preferred industry. The use of multiple measures that are thought to be correlated in order to test a phenomenon, can lead to the finding of spurious results. However, if the measures do actually measure different phenomena, despite that they are correlated, the results are less likely spurious. We present two correlation matrixes in the appendix. The first one presents the correlations between the performance measures. The other presents the correlations between all the explanatory and control variables. Assessing the correlation matrixes, we do not find correlations raising concerns regarding the use of several performance measures and specialization measures.

Table 5.1.1 Summary Statistics for variables included in our models

Variables	Obs	Mean	Std. Dev.	Min	Max
Dependent Variables					
Year 1 to 5					
Increased Profits	120	0.483	0.502	0	1
Increased Revenues	120	0.467	0.501	0	1
Revenue Growth	120	1.155	3.362	-9.404	10.077
Payroll Growth	120	0.858	2.892	-9.329	9.571
Productivity Growth	120	0.176	0.7994	-2.419	2.587
Year 1 to 3					
Increased Profits	120	0.467	0.501	0	1
Increased Revenues	120	0.567	0.498	0	1
Revenue Growth	120	0.929	2.788	-8.434	10.372
Payroll Growth	120	1.106	2.029	-3.279	8.164
Productivity Growth	120	0.174	0.664	-1.508	3.434
Year 3 to 5					
Increased Profits	120	0.483	0.502	0	1
Increased Revenues	120	0.500	0.502	0	1
Revenue Growth	120	0.227	2.869	-11.819	12.152
Payroll Growth	120	-0.248	1.956	-9.866	2.704
Productivity Growth	120	0.002	0.783	-4.322	2.684
Explanatory Variables					
Spec	120	1.555	0.954	0	5
Spec^2	120	3.320	3.909	0	25
Mostspecilzed	120	0.500	0.502	0	1
Match	120	1.501	1.436	0	6.667
Match^2	120	4.298	7.123	0	44.444
Bestmatch	120	0.500	0.502	0	1
Preferred Sector50	120	0.392	0.490	0	1
Preferred NHO50	120	0.317	0.467	0	1
Preferred NHO40	120	0.375	0.486	0	1
Preferred NHO30	120	0.492	0.502	0	1
Control Variables					
Joint Venture	120	0.142	0.350	0	1
Nr. Investment VC	120	8.042	4.689	3	22
Years Since Foundation	120	5.625	6.443	0	46
Years Since Foundation^2	120	72.808	209.525	0	2116
Patents Year 1	120	1298.033	4197.612	0	32360
Financial Bust	120	0.292	0.4564	0	1
Financial Bust Performance	120	0.258	0.439	0	1

5.2 Part I

Research question I: *How does the related specialization of a Venture Capital firm affect the performance of portfolio companies?*

In this part we make use of the measures of industry specialization based on the concentric index presented by Caves et al. (1980). We define these as measures of related specialization. We will analyse the effects on PC performance of both the degree of related specialization in a VC firm´s portfolio, and the portfolio relatedness between the existing portfolio of a VC firm and a PC becoming part of this portfolio. *Spec, Spec^2* and *Mostspecialized* are measures of the degree of related specialization. *Match, Match^2* and *Bestmatch* are measures of portfolio relatedness. The variables used in the regressions are described in detail in the methodology section. We analyse the effect of related specialization on the different performance measures in separate sections before summarizing and discussing the results.

A. Increased Profits

We start by conducting several regression models where we use *Increased Profits* as our dependent variable. In this case, we consider whether the different measures of related specialization affect the likelihood of a PC to experience increased profits. The results are reported in table 5.2.1-5.2.3. Considering the entire period, the results indicate that PCs backed by VC firms with a high degree of related specialization are more likely to experience increased profits in the five-year period following the initial investment. This result is statistically significant at a 10% level. Further, the PCs that are backed by the VC firms having the 50% highest degree of related specialization, i.e. the *Mostspecialized,* are more likely to experience increased profits during the entire period. This result is also statistically significant at a 10% level, and is in line with the result presented above.

Examining the results in the two sub-periods, we do not find any statistically significant results. However, examining the coefficients of *Spec*, *Spec^2* and *Mostspecialized* in the two sub periods we find that they are consistent with the findings covering the entire period. However, as these results are not statistically significant within a 10% level we cannot rely on these findings. The effect of different degrees of related specialization on the likelihood of experiencing increased profits is not more prominent in one sub-period than the other. This might be due to the process of increasing profits being a long lasting process, where the outcomes over time are more prominent than in the short run.

There are no statistically significant results concerning the effect of portfolio relatedness on the likelihood of PCs experiencing increased profits. In other words, the “match” between a new PC invested in by a VC firm and this VC firm´s existing portfolio does not seem to influence the likelihood of the PC experiencing increased profits.

Combining the results from the measures *Spec* and *Mostspecialized*, we may deduce that PCs that are backed by VC firms with a higher degree of related specialization are more likely to experience increased profits over the entire period than PCs backed by less specialized VC firms. Based on our findings we are unable to detect any significant relationship between the portfolio relatedness measures and the likelihood of achieving increased profits.

Table 5.2.1: Increased Profits. Year 1-5

VARIABLES	(1.logit) Increased Profits	(2.logit) Increased Profits	(3.logit) Increased Profits	(4.logit) Increased Profits
Spec	1.373*			
	(0.753)			
Spec^2	-0.294			
	(0.194)			
Mostspecialized		0.792*		
		(0.437)		
Match			0.189	
			(0.448)	
Match^2			-0.0420	
			(0.0953)	
Bestmatch				-0.0435
				(0.427)
Joint Venture	-0.977	-1.083*	-0.722	-0.742
	(0.649)	(0.647)	(0.637)	(0.629)
Nr. Investment VC	-0.0124	0.0174	0.00370	0.00799
	(0.0495)	(0.0468)	(0.0473)	(0.0462)
Years Since Foundation	0.124**	0.134**	0.115*	0.114*
	(0.0593)	(0.0589)	(0.0601)	(0.0601)
Years Since Foundation^2	-0.000830	-0.00114	-0.000876	-0.000840
	(0.00151)	(0.00148)	(0.00150)	(0.00151)
Patents Year 1	0.000163**	0.000161*	0.000166*	0.000166*
	(7.94e-05)	(8.79e-05)	(9.22e-05)	(9.70e-05)
Financial Bust	-0.115	-0.206	-0.185	-0.204
	(0.482)	(0.488)	(0.473)	(0.471)
Financial Bust Performance	0.980*	0.726	0.739	0.677
	(0.578)	(0.541)	(0.557)	(0.540)
Telecom, IT & Tech	0.543	0.423	0.600	0.646
	(0.621)	(0.609)	(0.628)	(0.598)
Wholesale & Retail	0.371	0.208	0.559	0.439
	(1.047)	(1.013)	(0.894)	(0.863)
Other Services	0.226	0.139	0.203	0.225
	(0.605)	(0.591)	(0.585)	(0.568)
Constant	-2.312***	-1.609**	-1.293*	-1.182*
	(0.851)	(0.649)	(0.664)	(0.658)
Observations	116	116	116	116
Pseudo R2	0.1267	0.1229	0.1044	0.1034

Pseudo R2: McFadden's Pseudo R2
Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1.
Transport and construction are omitted due to collinearity.
Offshore & Shipping, Electricity and Finance omitted due to perfect ability to predict failure/success and 4 observations not used.

Table 5.2.2: Increased Profits. Year 1-3

VARIABLES	(1.logit) Increased Profits	(2.logit) Increased Profits	(3.logit) Increased Profits	(4.logit) Increased Profits
Spec	0.274			
	(0.695)			
Spec^2	0.0330			
	(0.157)			
Mostspecialized		0.496		
		(0.484)		
Match			0.459	
			(0.505)	
Match^2			-0.0436	
			(0.0959)	
Bestmatch				0.551
				(0.470)
All Control Variables Included	Yes	Yes	Yes	Yes
Constant	-1.592**	-1.372**	-1.540**	-1.385**
	(0.770)	(0.613)	(0.640)	(0.615)
Observations	117	117	117	117
Pseudo R2	0.1060	0.0956	0.1050	0.0974

Pseudo R2: McFadden's Pseudo R2
Robust standard errors in parentheses. Significance levels denoted as *** p<0.01, ** p<0.05, * p<0.1
Transport omitted due to collinearity.
Electricity, Construction and Finance omitted due to perfect ability to predict success/failure and 3 observations not used.

Table 5.2.3: Increased Profits. Year 3-5

VARIABLES	(1.logit) Increased Profits	(2.logit) Increased Profits	(3.logit) Increased Profits	(4.logit) Increased Profits
Spec	0.830			
	(0.635)			
Spec^2	-0.229			
	(0.160)			
Mostspecialized		0.170		
		(0.422)		
Match			0.193	
			(0.435)	
Match^2			-0.0783	
			(0.0922)	
Bestmatch				-0.343
				(0.426)
All Controls Variables Included	Yes	Yes	Yes	Yes
Constant	-0.566	-0.134	-0.102	0.0881
	(0.746)	(0.651)	(0.681)	(0.660)
Observations	118	118	118	118
Pseudo R2	0.0597	0.0496	0.0602	0.0524

Pseudo R2: McFadden's Pseudo R2
Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport and construction omitted due to collinearity
Electricity and Finance omitted due to perfect ability to predict success/failure and 2 observations not used.

In this study, we analyse a somewhat short timeframe. Hence, we have to be cautious drawing conclusions about the performance of PCs solely based on their ability to increase profits. Once a VC firm has invested in a PC, its decisions on how to develop the PC may vary substantially depending on the nature of the PC, and the strategic goals set for the PC by the VC firm. There are several growth strategies that do not generate profits within a period as short as five years. Some firms rely on large investments in R&D before launching their product, while others will price their products or services below cost in order to increase sales and gain market shares. As many firms prioritize boosting revenues in the PCs over organic growth, other measures of performance are of interest. Nevertheless, going forward, we will keep the findings from section A in mind when analysing the results related to other performance measures.

B. Increased Revenues

This section investigates whether related specialization within a VC firm affects the likelihood for a PC to achieve increased revenues[8]. Doing this, we conduct the same regressions as in section A, this time using *Increased Revenues* as the dependent variable. The results of the regressions are reported in table 5.2.4-5.2.6. Analysing the results, we find that the *Mostspecialized* variable is statistically significant at a 10% level. In other words, PCs backed by VC firms with the 50 % highest degree of related specialization are more likely to increase their revenues over the entire period. When elaborating on this relationship by considering the period from year one to year three we find that the relationship is still prominent. However, this no longer holds true when considering the period from year three to year five. When analysing the effect of portfolio relatedness, we do not find any evidence suggesting that the "match" between the new PC and the existing portfolio of the VC firm affects the likelihood of achieving increased revenues.

Summarizing, we find evidence pointing towards that the PCs that are backed by the VC firms with the 50 % highest degree of related specialization are more likely to experience increased revenues in the period from year one to year five. This effect appears to be more prominent in the sub-period following the year of investment, compared to the second sub-period.

[8] In order to roughly divide our sample in two we define *Increased Revenues* as doubling the revenues from year 1-5, increasing the revenues by 40 % from year 1-3, and by 30 % from year 3-5.

The findings are interesting for several reasons. First, when comparing the results from section A and B there seems to be a positive relationship between the degree of related specialization and performance, both measured by *Increased Profits* and *Increased Revenues*. This indicates that the PCs backed by VC firms with a high degree of related specialization achieve increased profits due to the ability to increase revenues. Second, in A we did not find that the likelihood of experiencing increased profits differed between the two sub-periods. However, in section B we discovered that the likelihood of achieving increased revenues is more prominent in the first period. From this, we reason that increasing revenues in the first years after VC entrants are viewed to be more important than boosting profits. Similar to our findings when analysing increased profits, we do not find any evidence of portfolio relatedness affecting the likelihood of increased revenues.

Table 5.2.4: Increased Revenues - Year 1-5

VARIABLES	(logit) Increased Revenues	(logit) Increased Revenues	(logit) Increased Revenues	(logit) Increased Revenues
Spec	1.062			
	(0.673)			
Spec^2	-0.243			
	(0.165)			
Mostspecialized		0.789*		
		(0.442)		
Match			0.0699	
			(0.449)	
Match^2			-0.0432	
			(0.0911)	
Bestmatch				-0.397
				(0.440)
Joint Venture	-0.671	-0.910	-0.531	-0.612
	(0.667)	(0.670)	(0.643)	(0.625)
Nr. Investment VC	-0.111**	-0.0856*	-0.0949**	-0.0872**
	(0.0459)	(0.0448)	(0.0443)	(0.0436)
Years Since Foundation	0.0226	0.0420	0.0290	0.0321
	(0.106)	(0.107)	(0.109)	(0.110)
Years Since Foundation^2	-0.00409	-0.00490	-0.00512	-0.00543
	(0.00609)	(0.00614)	(0.00630)	(0.00646)
Patents Year 1	1.23e-05	-8.82e-06	1.05e-05	-3.21e-06
	(5.07e-05)	(4.26e-05)	(5.68e-05)	(4.60e-05)
Financial Bust	-0.259	-0.284	-0.331	-0.351
	(0.482)	(0.469)	(0.475)	(0.473)
Financial Bust Performance	-0.200	-0.396	-0.369	-0.514
	(0.553)	(0.535)	(0.533)	(0.541)
Telecom, IT & Tech	-0.359	-0.503	-0.133	-0.117
	(0.572)	(0.574)	(0.594)	(0.578)
Wholesale & Retail	-1.066	-1.282	-0.875	-1.061
	(1.063)	(1.083)	(1.067)	(1.037)
Other Services	-0.525	-0.595	-0.435	-0.452
	(0.592)	(0.598)	(0.596)	(0.588)
Constant	0.636	1.031	1.376*	1.517**
	(0.823)	(0.704)	(0.763)	(0.735)
Observations	116	116	116	116
Pseudo R2	0.0848	0.0895	0.0747	0.0739

Pseudo R2: McFadden's Pseudo R2
Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport and Construction omitted due to collinearity.
Offshore/shipping, Electricity and Finance omitted due to perfect ability to predict failure/success and 4 observations not used.

Table 5.2.5: Increased Revenues - Year 1-3

VARIABLES	(logit) Increased Revenues	(logit) Increased Revenues	(logit) Increased Revenues	(logit) Increased Revenues
Spec	0.515			
	(0.744)			
Spec^2	-0.0901			
	(0.201)			
Mostspecialized		0.850*		
		(0.477)		
Match			0.183	
			(0.467)	
Match^2			-0.0696	
			(0.0953)	
Bestmatch				-0.0266
				(0.465)
All Control Variables Included	Yes	Yes	Yes	Yes
Constant	0.420	0.501	0.801	0.829
	(0.796)	(0.661)	(0.732)	(0.683)
Observations	117	117	117	117
Pseudo R2	0.1002	0.1163	0.1034	0.0950

Pseudo R2: McFadden's Pseudo R2
Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport omitted due to collinearity
Electricity, Construction and Finance omitted due to perfect ability to predict success/failure and 3 observations not used

Table 5.2.6: Increased Revenues - Year 3-5

VARIABLES	(logit) Increased Revenues	(logit) Increased Revenues	(logit) Increased Revenues	(logit) Increased Revenues
Spec	-0.530			
	(0.725)			
Spec^2	0.128			
	(0.186)			
Mostspecialized		-0.0335		
		(0.439)		
Match			-0.501	
			(0.485)	
Match^2			0.125	
			(0.0976)	
Bestmatch				0.0522
				(0.437)
All Control Variables Included	Yes	Yes	Yes	Yes
Constant	1.925*	1.560**	1.824**	1.525**
	(0.999)	(0.773)	(0.856)	(0.759)
Observations	118	118	118	118
Pseudo R2	0.0835	0.0797	0.0915	0.0798

Pseudo R2: McFadden's Pseudo R2
Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport and construction omitted due to collinearity.
Electricity and finance omitted due to perfect ability to predict success/failure and two observations not used.

C. Revenue Growth

In this section we will use *Revenue Growth* as the dependent variable, and consider whether the different related specialization measures affect revenue growth in PCs. The results are reported in table 5.2.7-5.2.9. Differing from section B, we use a continuous variable. By doing so, we allow larger values in terms of revenue growth to be more influential. This was not the case in section B, as a binary variable to not differ between observations exceeding the threshold value with a small or a large margin.

Examining the results from the different models, we do not find any relationship that is statistically significant, at a 10% significance threshold, between the different variables of related specialization and revenue growth. These findings are consistent irrespectively of the choice of period. This suggests that the potential benefits of related specialization do not yield any difference in terms of revenue growth.

In sum, we are not able to infer that PCs backed by VC firms with different degrees of related specialization perform any different in terms of revenue growth. This conclusion can also be drawn when considering the portfolio relatedness between the PC and the already existing portfolio of the VC firm. This suggests that using revenues as a performance measure is sensitive to the choice of measurement specification.

Table 5.2.7: Revenue Growth - Year 1-5

VARIABLES	(1.OLS) Revenue Growth	(2.OLS) Revenue Growth	(3.OLS) Revenue Growth	(4.OLS) Revenue Growth
Spec	-0.348			
	(0.952)			
Spec^2	0.0331			
	(0.258)			
Mostspecialized		-0.470		
		(0.643)		
Match			-0.257	
			(0.710)	
Match^2			0.0324	
			(0.139)	
Bestmatch				-0.509
				(0.657)
Joint Venture	0.631	0.740	0.510	0.487
	(1.324)	(1.347)	(1.367)	(1.320)
Nr. Investment VC	-0.109	-0.116*	-0.108	-0.106
	(0.0687)	(0.0636)	(0.0678)	(0.0659)
Years Since Foundation	-0.199**	-0.205**	-0.199**	-0.204**
	(0.0846)	(0.0869)	(0.0854)	(0.0852)
Years Since Foundation^2	0.00412**	0.00423**	0.00419**	0.00434**
	(0.00176)	(0.00180)	(0.00181)	(0.00182)
Patent Year 1	7.05e-05	6.53e-05	6.40e-05	6.93e-05
	(7.29e-05)	(6.45e-05)	(7.51e-05)	(6.55e-05)
Financial Bust	-0.139	-0.107	-0.137	-0.167
	(0.652)	(0.668)	(0.649)	(0.646)
Financial Bust Performance	-1.091	-1.074	-1.124	-1.206
	(1.075)	(0.924)	(0.980)	(0.907)
Offshore & Shipping	-1.329	-1.312	-1.546	-1.520
	(1.316)	(1.175)	(1.316)	(1.222)
Telecom, IT & Tech	0.109	0.123	0.153	0.181
	(0.855)	(0.861)	(0.780)	(0.811)
Electricity	3.727***	3.742***	3.755***	3.739***
	(1.187)	(1.103)	(1.228)	(1.102)
Wholesale & Retail	-0.295	-0.329	-0.568	-0.562
	(2.760)	(2.621)	(2.785)	(2.728)
Finance	-1.073	-1.105	-1.320	-1.263
	(1.513)	(1.303)	(1.294)	(1.306)
Other Services	-0.869	-0.856	-0.844	-0.880
	(0.893)	(0.896)	(0.851)	(0.893)
Constant	3.691***	3.543***	3.525***	3.559***
	(1.183)	(0.941)	(1.016)	(0.924)
Observations	120	120	120	120
R-squared	0.118	0.118	0.116	0.118

Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Note: Construction and Transport omitted due to collinearity
Transport and Construction omitted due to collinearity

Table 5.2.8: Revenue Growth - Year 1-3

VARIABLES	(1.OLS) Revenue Growth	(2.OLS) Revenue Growth	(3.OLS) Revenue Growth	(4.OLS) Revenue Growth
Spec	-0.326			
	(0.921)			
Spec^2	0.0702			
	(0.217)			
Mostspecialized		-0.380		
		(0.597)		
Match			0.333	
			(0.484)	
Match^2			-0.0636	
			(0.117)	
Bestmatch				-0.0617
				(0.519)
All Control Variables Included	Yes	Yes	Yes	Yes
Constant	2.032*	1.951**	1.627*	1.826**
	(1.142)	(0.846)	(0.851)	(0.796)
Observations	120	120	120	120
R-squared	0.223	0.225	0.225	0.222

Robust standard errors in parentheses***. Significance levels denoted as: p<0.01, ** p<0.05, * p<0.1
Transport omitted due to collinearity

Table 5.2.9: Revenue Growth - Year 3-5

VARIABLES	(1.OLS) Revenue Growth	(2.OLS) Revenue Growth	(3.OLS) Revenue Growth	(4.OLS) Revenue Growth
Spec	-0.978			
	(0.861)			
Spec^2	0.161			
	(0.225)			
Mostspecialized		-0.598		
		(0.679)		
Match			-0.974	
			(0.661)	
Match^2			0.160	
			(0.119)	
Bestmatch				-0.714
				(0.665)
All Control Variables Included	Yes	Yes	Yes	Yes
Constant	2.429**	1.850**	2.232***	1.899**
	(1.007)	(0.764)	(0.828)	(0.754)
Observations	120	120	120	120
R-squared	0.153	0.144	0.159	0.147

Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport and Construction omitted due to collinearity

D. Payroll Growth

After having considered how related specialization of a VC firm affects the income streams in a PC, we would like to learn more about these effects by considering payroll growth in PCs. When analysing the effect of the different related specialization measures on payroll growth, we conduct the same regressions as in the previous sections, this time using *Payroll Growth* as the dependent variable. The results are illustrated in table 5.2.10-5.2.12. Examining the results, we discover several findings of interest. There seems to be a nonlinear relationship both between the degree of related specialization and payroll growth, and between portfolio relatedness and payroll growth. When analysing the former, it appears that there is a u-shaped relationship between the degree of related specialization in a VC firm and payroll growth in PCs. More precisely, this implies that the PCs that are supported either by a VC firm with a high or low degree of related specialization experience higher payroll growth than the portfolio companies that are backed by neither of the two groups. This relationship is statistically significant at a 10% level when considering the entire period, and at a 5% level when taking the second sub-period into account. However, the relationship is not statistically significant when studying the first sub-period. In other words, the effect of specialization on payroll growth is more prominent in the latter sub-period. This indicates that it takes time for the benefits of related specialization within a VC firm to have an effect on payroll growth in a PC.

The u-shaped relationship is also present when considering the portfolio relatedness between a new PC and the existing portfolio of a VC firm. As in the case of the degree of related specialization, it seems to be a threshold of portfolio relatedness, implying that both a "mismatch" and a good "match" yields higher payroll growth then neither of the two cases. This result is significant at a 5% level both when considering the entire period and the second sub-period.

In sum, the degree of related specialization in a VC firm, as well as the portfolio relatedness between the new PC and the existing portfolio of a VC firm, seems to affect payroll growth. The two effects are more prominent in the second sub-period compared to the first. The degree of related specialization and portfolio relatedness being statistically significant on payroll growth is in contrast to our findings in section C, where we did not find any support when investigating the effect of the same specialization measures on revenue growth.

Table 5.2.10: Payroll Growth - Year 1-5

VARIABLES	(1.OLS) Payroll Growth	(2.OLS) Payroll Growth	(3.OLS) Payroll Growth	(4.OLS) Payroll Growth
Spec	-1.595*			
	(0.869)			
Spec^2	0.436*			
	(0.240)			
Mostspecialized		-0.0917		
		(0.573)		
Match			-1.196**	
			(0.533)	
Match^2			0.261**	
			(0.118)	
Bestmatch				-0.347
				(0.551)
Joint Ventures	-1.228	-1.229	-1.521	-1.303
	(0.858)	(0.901)	(0.934)	(0.952)
Nr. Investment VC	-0.00797	-0.0448	-0.0207	-0.0404
	(0.0552)	(0.0502)	(0.0506)	(0.0497)
Years Since Foundation	-0.254***	-0.248***	-0.253***	-0.252***
	(0.0764)	(0.0779)	(0.0772)	(0.0768)
Years Since Foundation^2	0.00495***	0.00499***	0.00519***	0.00513***
	(0.00171)	(0.00174)	(0.00178)	(0.00176)
Patent Year 1	-9.45e-05	-3.88e-05	-0.000104	-3.51e-05
	(0.000105)	(0.000110)	(0.000107)	(0.000114)
Financial Bust	0.424	0.445	0.420	0.401
	(0.595)	(0.609)	(0.584)	(0.588)
Financial Bust Performance	-0.699	-0.341	-0.658	-0.433
	(0.750)	(0.683)	(0.729)	(0.700)
Offshore & Shipping	2.493**	1.839*	1.557	1.738
	(0.987)	(0.973)	(1.006)	(1.054)
Telecom, IT & Tech	-0.310	-0.261	-0.0915	-0.157
	(0.723)	(0.751)	(0.698)	(0.693)
Electricity	2.700**	3.223***	2.514**	3.133***
	(1.089)	(1.027)	(1.068)	(1.051)
Wholesale & Retail	-1.584	-1.353	-2.119	-1.435
	(2.242)	(2.261)	(2.280)	(2.262)
Finance	0.782	0.219	-0.0204	0.155
	(1.270)	(1.239)	(1.151)	(1.214)
Other Services	-0.555	-0.519	-0.418	-0.507
	(0.695)	(0.696)	(0.665)	(0.684)
Constant	3.691***	2.762***	3.375***	2.875***
	(1.097)	(0.852)	(0.910)	(0.887)
Observations	120	120	120	120
R-squared	0.201	0.173	0.207	0.176

Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport and Construction omitted due to collinearity

Table 5.2.11: Payroll Growth - Year 1-3

VARIABLES	(1) Payroll Growth	(2) Payroll Growth	(3) Payroll Growth	(4) Payroll Growth
Spec	-0.612			
	(0.694)			
Spec^2	0.0994			
	(0.155)			
Mostspecialized		-0.116		
		(0.438)		
Match			-0.305	
			(0.422)	
Match^2			0.0589	
			(0.0942)	
Bestmatch				-0.0806
				(0.349)
All Control Variables Included	Yes	Yes	Yes	Yes
Constant	2.377**	1.922***	2.037**	1.907**
	(0.969)	(0.721)	(0.781)	(0.728)
Observations	120	120	120	120
R-squared	0.291	0.279	0.282	0.278

Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport omitted due to collinearity

Table 5.2.12: Payroll Growth - Year 3-5

VARIABLES	(1) Payroll Growth	(2) Payroll Growth	(3) Payroll Growth	(4) Payroll Growth
Spec	-1.267**			
	(0.633)			
Spec^2	0.400**			
	(0.183)			
Mostspecialized		-0.0325		
		(0.379)		
Match			-1.056**	
			(0.428)	
Match^2			0.234***	
			(0.0831)	
Bestmatch				-0.360
				(0.460)
Constant	1.207**	0.579	1.135**	0.725
	(0.608)	(0.457)	(0.508)	(0.499)
Observations	120	120	120	120
R-squared	0.187	0.126	0.187	0.133

Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport and Construction omitted due to collinearity

E. Productivity Growth

By now, we have uncovered results indicating that the related specialization of a VC firm has an impact on payroll growth, but not on revenue growth. We combine these two performance measures when using *Productivity Growth* as the dependent variable. In this thesis, productivity refers to labour productivity defined as revenues to payroll. The results of the regressions are provided in table 5.2.13-5.2.15.

Evaluating the results, we find little evidence of any clear relationship between the measures of related specialization and productivity growth. However, from table 5.2.14 we find that the variable *Bestmatch* is statistically significant at a 10% level. This tells us that the PCs with the 50 % highest portfolio relatedness with the VC firms portfolio, experience lower productivity growth from year one to three than those who are not. This result is marginally statistically significant, with a p-value of 9,7 %.

In sum, when analysing the effects of related specialization in VC firms on productivity growth in PCs over the entire period, we do not find any results of statistically significance. This holds true for both sub-periods considering the degree of related specialization. However, we do find a negative statistically significant relationship between the variable *Bestmatch* and *Productivity Growth*, in the first sub-period. In section C and D, we did not find any statistically significant effects of related specialization on neither revenue growth, nor payroll growth in the first sub-period. We will elaborate on the negative effect of *Bestmach* on *Productivity Growth* in the summary.

Table 5.2.13: Productivity Growth - Year 1-5

VARIABLES	(1) Productivity Growth	(2) Productivity Growth	(3) Productivity Growth	(4) Productivity Growth
Spec	0.0387			
	(0.203)			
Spec^2	-0.00892			
	(0.0549)			
Mostspecialized		-0.0800		
		(0.161)		
Match			0.0786	
			(0.153)	
Match^2			-0.0216	
			(0.0315)	
Bestmatch				-0.195
				(0.166)
Joint Ventures	0.00917	0.0468	0.0338	-0.00732
	(0.240)	(0.253)	(0.243)	(0.243)
Nr. Investment VC	-0.0239	-0.0239	-0.0251*	-0.0212
	(0.0146)	(0.0151)	(0.0151)	(0.0154)
Years Since Foundation	-0.0235	-0.0256	-0.0239	-0.0274
	(0.0191)	(0.0194)	(0.0192)	(0.0192)
Years Since Foundation^2	0.000661*	0.000688*	0.000659	0.000762*
	(0.000398)	(0.000399)	(0.000398)	(0.000396)
Patent Year 1	3.39e-06	2.90e-06	9.52e-06	4.85e-06
	(2.19e-05)	(1.68e-05)	(2.29e-05)	(1.75e-05)
Financial Bust	-0.242	-0.244	-0.247	-0.269
	(0.168)	(0.169)	(0.165)	(0.163)
Financial Bust Performance	-0.274	-0.282	-0.258	-0.334
	(0.237)	(0.215)	(0.224)	(0.214)
Offshore & Shipping	-0.777*	-0.749**	-0.763*	-0.810**
	(0.408)	(0.348)	(0.401)	(0.377)
Telecom, IT & Tech	0.300	0.325*	0.312*	0.376*
	(0.187)	(0.195)	(0.186)	(0.190)
Electricity	0.758***	0.711***	0.789***	0.671***
	(0.237)	(0.234)	(0.246)	(0.244)
Wholesale & Retail	0.146	0.174	0.209	0.118
	(0.551)	(0.525)	(0.560)	(0.559)
Finance	-0.160	-0.131	-0.146	-0.172
	(0.306)	(0.280)	(0.286)	(0.282)
Other Services	-0.159	-0.148	-0.157	-0.145
	(0.207)	(0.206)	(0.200)	(0.203)
Constant	0.500**	0.563***	0.494**	0.614***
	(0.232)	(0.205)	(0.208)	(0.197)
Observations	120	120	120	120
R-squared	0.132	0.134	0.136	0.144

Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport and Construction omitted due to collinearity

Table 5.2.14: Productivity Growth - Year 1-3

VARIABLES	(1) Productivity Growth	(2) Productivity Growth	(3) Productivity Growth	(4) Productivity Growth
Spec	-0.0616			
	(0.221)			
Spec^2	0.0149			
	(0.0518)			
Mostspecialized		-0.0667		
		(0.144)		
Match			-0.0580	
			(0.118)	
Match^2			0.00845	
			(0.0246)	
Bestmatch				-0.170*
				(0.102)
All Control Variables Included	Yes	Yes	Yes	Yes
Constant	0.544**	0.530***	0.540***	0.569***
	(0.252)	(0.196)	(0.193)	(0.192)
Observations	120	120	120	120
R-squared	0.173	0.175	0.174	0.185

Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport omitted due to collinearity.

Table 5.2.15: Productivity Growth - Year 3-5

VARIABLES	(1) Productivity Growth	(2) Productivity Growth	(3) Productivity Growth	(4) Productivity Growth
Spec	-0.0440			
	(0.207)			
Spec^2	0.0128			
	(0.0553)			
Mostspecialized		-0.0578		
		(0.148)		
Match			0.0743	
			(0.148)	
Match^2			-0.0180	
			(0.0284)	
Bestmatch				-0.0575
				(0.164)
All Other Variables Included	Yes	Yes	Yes	Yes
Constant	0.159	0.160	0.0975	0.160
	(0.221)	(0.205)	(0.206)	(0.216)
Observations	120	120	120	120
R-squared	0.147	0.148	0.149	0.148

Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport and Construction omitted due to collinearity

Summary and Discussion Part I

The purpose of Part I was to analyse how industry specialization, measured by related specialization of VC firms, affects performance in PCs. Examining the results, we find evidence suggesting a strict positive relationship between the degree of related specialization of a VC firm and the likelihood for a PC to achieve increased profits. Further, we find no evidence suggesting that the degree of related specialization affects revenue growth. However, this result contrasts with the finding in which suggests that PCs that are backed by VC firms with the 50% highest degree of related specialization are more likely to experience increased revenues over the entire period. This effect appears to be more prominent in the sub-period following the year of investment, compared to the second sub-period. When investigating an important driver for costs in PCs, namely payroll expenses, we find that both the degree of related specialization within a VC firm, and the portfolio relatedness between the new PC and the existing portfolio of the VC firm, affects payroll growth. In these cases, we observe a u-shaped relation. The two effects are more prominent in the second sub period compared to the first. Taking both revenues and payroll growth into consideration we analysed productivity growth. Doing this, we find little evidence suggesting any clear relationship between related specialization and productivity growth. However, we find a statistically significant relationship between the variable *Bestmatch* and productivity growth, in the first sub period. The statistically significant results found in part I, when applying a 10% significance threshold, is displayed in table 5.2.16.

Table 5.2.16: Statistically significant results from part I. Applying a 10 % significance level

	Increased Profits	Increased Revenues	Revenue Growth	Payroll Growth	Productivity Growth
Spec	+ $*_1$			$-*_1$, $-**_3$	
Spec^2				$+*_1$, $+**_3$	
Mostspecialized	$+*_1$	$+*_1$, $+*_2$			
Match				$-**_1$, $-**_3$	
Match^2				$+**_1$, $+***_3$	
Bestmatch					$-*_2$

+/-=Sign of the coefficient
Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
1=Year 1-5, 2=Year 1-3, 3=Year 3-5

When combining the results from part I, we are able to detect a somewhat positive relationship between industry specialization of VC firms and the performance in PCs.

The ability to increase profits and revenues is unarguably positive for a PC, and the results from section A and B indicate a positive relationship between the related specialization of a VC firm and the performance of PCs. That is, PCs being backed by VC firms with a high degree of industry specialization, i.e. degree of related specialization, obtain higher performance. These results are in line with the model presented by Montgomery and Wernerfelt (1988) describing the relationship between specialized factors, their area of use and the rents to the use of the factors. Following their arguments, the reason why the PCs backed by more specialized VCs obtain higher performance than PCs, backed by less specialized VCs, is that specific resources yields higher rents than less specific resources. The VCs with higher degree of industry specialization possess specific resources such as industry experience, a more complete network within the industry and access to superior information. These resources gains higher rents than more general resources when used in industries close to the industry in which the resource originated (Montgomery & Wernerfelt, 1988).

As discussed in section B, the positive effect of being backed by a VC firm with high related specialization, appears to be more prominent in the first sub-period, when considering the likelihood of a PC to experience increased revenues. Even though we seek to control for selection effects, we might fail to capture the entire effect. Hence, one might argue that more specialized VC firms are able to discover and invest in PCs with promising growth characteristics and unexploited potential, resulting in a sharp increase in revenues in the first years after the investment. Moreover, one might reason that this effect turns insignificant in the second sub period as the potential is being exploited primarily in the first years after the investment. Leaning too heavily on this reasoning is a bit controversial as the findings might also have other explanations. Some PCs might, for instance, prioritize ramping up income streams in the first years after the VC entry, resulting in the findings observed.

Payroll growth can be viewed as a positive indicator when assessing the performance of a growth company, as it might indicate increased present or future demand for the company´s services or products. In section D we found nonlinear relationships between industry specialization, measured by the degree of related specialization and portfolio relatedness, and payroll growth. The u-shaped relationship indicates that PCs have higher performance if they are backed by VC firms with either a high or a low degree of industry specialization.

Montgomery and Wernerfelt (1988) describes a mechanism that can lead to this outcome. Their model allows less specific resources to provide superior rents than more specific resources when the distance to the industry in which the resources originated becomes large. The argument is that specific resources at some point become less useful than more general resources when moving further and further away from the industry of these resources´ origin. Relating to the VC industry, such more general resources can be management, consulting or marketing experience. Opposed to this view, the positive effect of a low degree of industry specialization on PC performance may be the result of other forms of specialization rather than industry diversification. Such specialization can be VC firms specialized in supporting PCs in given situations, such as PCs seeking to undergo profound changes in near future. Another possible explanation to why one observes the U-shaped relationship is that VC firms may specialize in niches which are not present in the NACE system, or in industries spanning across multiple industry categorizations in NACE system.

The same U-shaped relationship is also present when considering portfolio relatedness and payroll growth. This indicates that both a "mismatch" and a "good match", i.e. both difference and similarity between the new PC and the existing portfolio of the VC, have a positive effect on payroll growth. Arguing for the former case, there are two possible explanations. First, diversified VC firms might be able to generate value through investing in ventures that will have a large benefit of their generalist resources. Second, it might be that specialized VCs occasionally discover and invest in some highly promising PCs with huge growth prospects, outside their core area of competence. Arguing for the latter case, the new entrant and the existent portfolio is a "good match" and the PC can benefit from having access to specific resources enhancing its performance, that enables the PC to increase its investments in labour. The U-shaped relation is similar to the findings discovered by Matusik and Fitza (2012). They find that there is a U-shaped relationship between VC diversification and performance.

When analysing *Productivity Growth,* we are not able to find any clear evidence of a relationship between related specialization and productivity growth. We find a negative relationship between the variable *Bestmatch* and the productivity growth in a PC when considering the period from year one to year three. This result is statistically significant with a p-value of 9,7 %. As earlier described, a VC´s decisions on how to develop a PC may vary substantially depending on the nature of the PC, and the strategic goals set for the PC by the VC firm. A strategy resulting in higher payroll growth than revenue growth, will result in poor performance measured by productivity growth. However, the PC might be at a stage in its lifecycle in which it requires employment growth even though it is not able to increase revenues in an equal pace. Further, a PC can decide to shift the focus from sales to development of new products. This will, in turn, result in a negative productivity growth as the revenues decrease, while the payroll expenses remain unchanged. These examples illustrate that a negative productivity growth is not necessarily equivalent to poor performance. In some cases, it may even be a positive sign.

To briefly summarize our findings in part I, we find evidence suggesting a positive relationship between the degree of industry specialization in a VC firm and PC performance. This is in line with the view of Wernerfelt and Montgomery (1988), arguing that more specific resources yields higher rents than less specific resources.

In this part, we have found what seems to be a positive relationship between the industry specialization of a VC firm and PC performance. In part II, we will analyse the effects of industry specialization within a VC firm further, by studying the effects of specialization at different industry levels on PC performance.

5.3 Part II

Research question II: *How does a Venture Capital firms´ specialization at a given industry level affect the performance of portfolio companies?*

In order to answer research question II, we need to answer two different questions. First, we will study at what industry level one must specialize in order to benefit from the positive effects of industry specialization identified in part I. Second, we will investigate if there is a threshold to how specialized a VC firm needs to be within that industry level to benefit from these effects.

Aiming at answering research question II, we have constructed different dummy variables that capture the effects of industry level specialization. We construct two sets of dummy variables. One that expresses specialization at sector level, and the other at NHO level. They are included in order to analyse sub-question I. The sector dummy is only reported with a 50 % threshold value[9]. The NHO variables are specified with either 50, 40 or 30 indicating the percentage of previous investments undertaken by the VC firm in a given NHO. We include these percentage levels seeking to answer our second sub-question. The dummy variables that are used in the regressions are described in detail in the methodology section.

Similar to our approach when considering research question I, we conduct the same regressions, while changing the related specialization measures on the right side of the regressions with the dummy variables described above. As in part I, we will analyse each of the performance measures individually, as well as considering the results when taking different time periods into account.

[9] As we do not find any effect of industry level specialization at sector level, we will not report different threshold values. We have also conducted the regressions with threshold value of 40 %. Similar to a threshold value of 50 %, this does not affect performance in PCs. Requiring 60 % of the previous investments leaves us with too few observations for comparison.

A. Increased Profits

Similar to our approach in part I, we will start by examining the performance measure *Increased Profits.* We will investigate whether industry level specialization of a VC firm affects the likelihood for a PC to achieve increased profits. Table 5.3.1-5.3.3 displays the results from the regressions. Starting by considering the entire period we do not find any results of statistical significance. This suggests that neither specialization at sector level, nor NHO level increases the likelihood for a PC to achieve increased profits when considering the entire period. The effect of industry level specialization at sector level remains insignificant irrespectively of the choice of period. However, when inspecting the first sub-period we find that all the *Preferred NHO* variables are positive and statistically significant at a 5% level. This indicates that the PCs operating in the NHO in which the VC firm is specialized experience higher profits than those operating in other NHOs.

To summarize, we do not find support for the presence of an effect of industry specialization at sector level on the likelihood of a PCs to experience increased profits. We find support that this is the case for specialization at NHO level. Though, only in the first sub-period. We find support for industry specialization having an effect on increased profits when 30% or more of the previous investments of the VC firm has been made in the same NHO. We cannot conclude with regards to the threshold value due to sample size restrictions[10].

[10] We do not analyse a threshold value of 20% as this leaves us with too few observations for comparison.

Table 5.3.1: Increased Profits - Year 1-5

VARIABLES	(1) Increased Profits	(2) Increased Profits	(3) Increased Profits	(4) Increased Profits
Preferred Sector50	-0.230			
	(0.423)			
Preferred NHO50		0.556		
		(0.484)		
Preferred NHO40			0.548	
			(0.456)	
Preferred NHO30				0.0220
				(0.428)
Joint Ventures	-0.758	-0.652	-0.620	-0.735
	(0.625)	(0.641)	(0.649)	(0.631)
Nr. Investment VC	0.00619	0.0223	0.0151	0.00800
	(0.0459)	(0.0495)	(0.0471)	(0.0465)
Years Since Foundation	0.115*	0.123**	0.122**	0.115*
	(0.0598)	(0.0605)	(0.0597)	(0.0597)
Years Since Foundation^2	-0.000923	-0.00120	-0.00115	-0.000859
	(0.00149)	(0.00149)	(0.00148)	(0.00150)
Patents Year 1	0.000160*	0.000167*	0.000163*	0.000166*
	(9.50e-05)	(9.19e-05)	(9.33e-05)	(9.66e-05)
Financial Bust	-0.215	-0.0972	-0.105	-0.195
	(0.471)	(0.479)	(0.479)	(0.476)
Financial Bust Performance	0.677	0.835	0.842	0.695
	(0.539)	(0.583)	(0.579)	(0.547)
Telecom, IT & Tech	0.722	0.574	0.534	0.624
	(0.581)	(0.595)	(0.603)	(0.607)
Wholesale & Retail	0.425	0.575	0.569	0.454
	(0.866)	(0.883)	(0.885)	(0.862)
Other Services	0.246	0.284	0.276	0.220
	(0.569)	(0.570)	(0.571)	(0.572)
Constant	-1.122*	-1.607**	-1.560**	-1.217*
	(0.658)	(0.730)	(0.687)	(0.655)
Observations	116	116	116	116
Pseudo R2	0.1051	0.1119	0.1126	0.1034

Pseudo R2: McFadden's Pseudo R2
Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport and Construction omitted due to collinearity
Offshore & Shipping, Electricity and Finance omitted due to perfect ability to predict failure/success, and 4 observations not used.

Table 5.3.2: Increased Profits - Year 1-3

VARIABLES	(1) Increased Profits	(2) Increased Profits	(3) Increased Profits	(4) Increased Profits
Preferred Sector50	0.326			
	(0.467)			
Preferred NHO50		1.142**		
		(0.456)		
Preferred NHO40			1.185***	
			(0.452)	
Preferred NHO30				1.163**
				(0.472)
All Control Variables Included	Yes	Yes	Yes	Yes
Constant	-1.251**	-1.969***	-1.929***	-1.899***
	(0.609)	(0.676)	(0.667)	(0.682)
Observations	117	117	117	117
Pseudo R2	0.0918	0.1239	0.1301	0.1298

Pseudo R2: McFadden's Pseudo R2
Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport omitted due to collinearity.
Electricity, Construction and Finance omitted due to perfect ability to predict failure/success and 3 observations not used.

Table 5.3.3: Increased Profits - Year 3-5

VARIABLES	(1) Increased Profits	(2) Increased Profits	(3) Increased Profits	(4) Increased Profits
Preferred Sector50	-0.355			
	(0.424)			
Preferred NHO50		-0.0590		
		(0.443)		
Preferred NHO40			0.0281	
			(0.419)	
Preferred NHO30				-0.310
				(0.403)
All Control Variables Included	Yes	Yes	Yes	Yes
Constant	0.0522	-0.0194	-0.0726	0.126
	(0.644)	(0.691)	(0.670)	(0.673)
Observations	118	118	118	118
Pseudo R2	0.0528	0.0487	0.0486	0.0520

Pseudo R2: McFadden's Pseudo R2
Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport and Construction omitted due to collinearity.
Electricity and Finance omitted due to perfect ability to predict success/failure and two observations not used.

B. Increased Revenues

In this section we will make use of our second binary performance measure, namely *Increased Revenues.* By this, we pursue to further analyse the effect of industry level specialization on performance in PCs. The results are reported in table 5.3.4- 5.3.6. There are no statistically significant results when analysing the effect of industry level specialization on the likelihood to experience increased profits over the entire period. With regards to specialization on sector level, this holds true for the two sub-periods as well. However, when studying the second sub-period we find that the *Preferred NHO50* variable and the *Preferred NHO40* variable are positive and statistically significant at a 5% and 1 % level, respectively. This indicates that new PCs operating in the same NHO as more than 40% of the VC firm´s previous investments operate in, will have a higher likelihood of experiencing increased revenues compared to the PCs who do not. When studying the NHO variables in the second sub-period we notice that the *Preferred NHO30* variable is not statistically significant. This indicates that in order for NHO level specialization to have an effect on PCs likelihood of increased revenues it requires that at least 40 % of previous investments are within the same NHO as the PC in question.

In sum, there is no evidence of an effect, of specialization on sector level, on the likelihood of PCs to experience increased revenues from year one to five. This is in line with the findings from section A. We do find a positive relationship between specialization at NHO level and the likelihood of a PC obtaining increased revenues. This result is however, only statistically significant in the second of the sub-periods. The *Preferred NHO30* variable is not statistically significant, supporting 40% as a threshold value for the benefits of NHO level specialization to be exploited.

Table 5.3.4: Increased Revenues - Year 1-5

VARIABLES	(1) Increased Revenues	(2) Increased Revenues	(3) Increased Revenues	(4) Increased Revenues
Preferred Sector50	-0.512			
	(0.426)			
Preferred NHO50		0.429		
		(0.445)		
Preferred NHO40			0.613	
			(0.425)	
Preferred NHO30				-0.0898
				(0.403)
Joint Ventures	-0.622	-0.512	-0.448	-0.578
	(0.646)	(0.658)	(0.672)	(0.644)
Nr. Investment VC	-0.0956**	-0.0804*	-0.0855**	-0.0912**
	(0.0435)	(0.0436)	(0.0429)	(0.0442)
Years Since Foundation	0.0429	0.0275	0.0315	0.0253
	(0.111)	(0.107)	(0.108)	(0.108)
Years Since Foundation^2	-0.00603	-0.00481	-0.00507	-0.00466
	(0.00660)	(0.00620)	(0.00632)	(0.00621)
Patents Year 1	-7.15e-06	-1.07e-05	-1.61e-05	-6.40e-06
	(4.52e-05)	(4.34e-05)	(4.31e-05)	(4.41e-05)
Financial Bust	-0.340	-0.215	-0.179	-0.315
	(0.482)	(0.473)	(0.475)	(0.473)
Financial Bust Performance	-0.422	-0.315	-0.274	-0.414
	(0.509)	(0.514)	(0.515)	(0.523)
Telecom, IT & Tech	-0.0638	-0.325	-0.409	-0.238
	(0.585)	(0.544)	(0.543)	(0.559)
Wholesale & Retail	-1.024	-0.942	-0.923	-1.029
	(1.039)	(1.078)	(1.108)	(1.038)
Other Services	-0.428	-0.456	-0.449	-0.479
	(0.592)	(0.588)	(0.592)	(0.589)
Constant	1.511**	1.096	1.038	1.404*
	(0.723)	(0.740)	(0.720)	(0.739)
Observations	116	116	116	116
Pseudo R2	0.0774	0.0746	0.0814	0.0692

Pseudo R2: McFadden's Pseudo R2
Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport & Construction omitted due to collinearity
Offshore & Shipping, Electricity and Finance omitted due to perfect ability to predict failure/success, and 4 observations not used.

Table 5.3.5: Increased Revenues - Year 1-3

VARIABLES	(1) Increased Revenues	(2) Increased Revenues	(3) Increased Revenues	(4) Increased Revenues
Preferred Sector50	-0.679 (0.486)			
Preferred NHO50		0.174 (0.482)		
Preferred NHO40			0.198 (0.463)	
Preferred NHO30				0.107 (0.451)
All Control Variables Included	Yes	Yes	Yes	Yes
Constant	1.022 (0.706)	0.709 (0.728)	0.708 (0.712)	0.763 (0.710)
Observations	117	117	117	117
Pseudo R2	0.1082	0.0958	0.0962	0.0953

Pseudo R2: McFadden's Pseudo R2
Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport omitted due to collinearity
Electricity, Construction and Finance due to perfect ability to predict failure/success, and 3 observations not used.

Table 5.3.6: Increased Revenues - Year 3-5

VARIABLES	(1) Increased Revenues	(2) Increased Revenues	(3) Increased Revenues	(4) Increased Revenues
Preferred Sector50	-0.237 (0.433)			
Preferred NHO50		1.120** (0.458)		
Preferred NHO40			1.320*** (0.436)	
Preferred NHO30				0.247 (0.409)
All Control Variables Included	Yes	Yes	Yes	Yes
Constant	1.614** (0.756)	0.939 (0.772)	0.966 (0.766)	1.416* (0.779)
Observations	118	118	118	118
Pseudo R2	0.0815	0.1153	0.1312	0.0817

Pseudo R2: McFadden's Pseudo R2
Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport and Construction omitted due of collinearity.
Electricity and Finance omitted due to perfect ability to predict failure/success, and 2 observations not used.

C. Revenue Growth

Continuing, we investigate the effects on *Revenue Growth*. The results are reported in table 5.3.7- 5.3.9. The results indicate that industry specialization at sector level has no statistically significant effect on revenue growth. The effect turns significant once evaluating industry specialization at NHO level. Elaborating this further we find that a PC owned by a VC firm with more than 40% of their previous investments in the same NHO as the NHO of the PC in question, experience higher revenue growth, considering the entire period. This relationship is statistically significant at a 5% level. These variables are positive but insignificant taking the two sub periods into account.

In terms of revenue growth, we find evidence suggesting that 40% of previous investment in the same NHO can be perceived as a threshold, enabling exploiting of benefits related to specialization at NHO level. We are able to infer this relation, as the *Preferred NHO30* variable is not statistically significant within a 10% significance threshold.

Summarizing, it is worth highlighting some findings. First, when addressing sub question one, we find that VC firm specialization at sector level does not affect revenue growth in PCs. Second, we find evidence that VC firm specialization at NHO level yields higher revenue growth in PCs backed by VC firms with relevant industry specialization than those who do not. Second, concerning sub question two, we find that it requires at least 40% of previous investments to be in the same NHO as the NHO of the PC in question, in order to exploit the benefits related to specialization at NHO level.

Table 5.3.7: Revenue Growth - Year 1-5

VARIABLES	(1) Revenue Growth	(2) Revenue Growth	(3) Revenue Growth	(4) Revenue Growth
Preferred Sector50	0.322			
	(0.671)			
Preferred NHO50		1.547**		
		(0.625)		
Preferred NHO40			1.458**	
			(0.579)	
Preferred NHO30				0.150
				(0.593)
Joint Ventures	0.564	0.754	0.845	0.553
	(1.332)	(1.278)	(1.289)	(1.336)
Nr. Investment VC	-0.109*	-0.0755	-0.0946	-0.108*
	(0.0639)	(0.0635)	(0.0621)	(0.0618)
Years Since Foundation	-0.194**	-0.182**	-0.181**	-0.194**
	(0.0830)	(0.0824)	(0.0825)	(0.0824)
Years Since Foundation^2	0.00413**	0.00328*	0.00339*	0.00403**
	(0.00176)	(0.00173)	(0.00174)	(0.00176)
Patents Year 1	6.24e-05	4.81e-05	4.11e-05	6.26e-05
	(6.61e-05)	(6.83e-05)	(6.88e-05)	(6.50e-05)
Financial Bust	-0.0734	0.202	0.182	-0.0702
	(0.651)	(0.652)	(0.651)	(0.643)
Financial Bust Performance	-1.056	-0.789	-0.787	-1.043
	(0.936)	(0.890)	(0.890)	(0.914)
Offshore & Shipping	-1.318	-0.955	-0.930	-1.350
	(1.215)	(1.244)	(1.267)	(1.232)
Telecom, IT & Tech	-0.143	-0.189	-0.299	-0.0574
	(0.820)	(0.879)	(0.873)	(0.844)
Electricity	3.993***	4.408***	4.387***	3.972***
	(1.053)	(1.027)	(1.036)	(1.056)
Wholesale & Retail	-0.470	-0.177	-0.209	-0.450
	(2.663)	(2.589)	(2.586)	(2.689)
Finance	-1.139	-0.940	-1.054	-1.159
	(1.297)	(1.329)	(1.317)	(1.331)
Other Services	-0.945	-0.786	-0.804	-0.930
	(0.905)	(0.929)	(0.933)	(0.898)
Constant	3.228***	2.369**	2.506***	3.242***
	(0.918)	(0.950)	(0.946)	(0.918)
Observations	120	120	120	120
R-squared	0.116	0.152	0.151	0.114

Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Construction omitted due to collinearity

Table 5.3.8: Revenue Growth - Year 1-3 (Compressed table output)

VARIABLES	(1) Revenue Growth	(2) Revenue Growth	(3) Revenue Growth	(4) Revenue Growth
Preferred Sector50	0.391			
	(0.523)			
Preferred NHO50		0.833		
		(0.575)		
Preferred NHO40			0.480	
			(0.512)	
Preferred NHO30				0.537
				(0.543)
All Control Variables Included	Yes	Yes	Yes	Yes
Constant	1.697**	1.281	1.531*	1.500*
	(0.760)	(0.859)	(0.836)	(0.829)
Observations	120	120	120	120
R-squared	0.226	0.238	0.228	0.230

Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport omitted due to collinearity

Table 5.3.9: Revenue Growth - Year 3-5

VARIABLES	(1) Revenue Growth	(2) Revenue Growth	(3) Revenue Growth	(4) Revenue Growth
Preferred Sector50	-0.289			
	(0.628)			
Preferred NHO50		0.580		
		(0.619)		
Preferred NHO40			0.850	
			(0.571)	
Preferred NHO30				-0.617
				(0.587)
All Control Variables Included	Yes	Yes	Yes	Yes
Constant	1.673**	1.220	1.099	1.950**
	(0.724)	(0.796)	(0.774)	(0.787)
Observations	120	120	120	120
R-squared	0.137	0.142	0.152	0.145

Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1Transport and Construction omitted due to collinearity

D. Payroll Growth

Continuing, we consider the effect of different levels of industry specialization on *Payroll Growth*. Doing this we conduct the same regressions as is section C, this time using *Payroll Growth* as the dependent variable. The results are illustrated in table 5.3.10-5.3.12. There are no statistically significant results when considering the entire period. This counts for all of the variables irrespectively of industry level. From the second sub-period we find that *Preferred NHO50* and *Preferred NHO40* is statistically significant at a 5% level. From this we infer that PCs backed by VC firms with relevant industry specialization at NHO level has higher payroll growth than those who do not, in the period from three to five years after VC entry. This is coherent with the results from a similar discussion in Part I, which suggested that the effect of specialization on payroll growth is more prominent in the second sub-period in comparison to the first.

Summarizing, we do not find support for the presence of an effect of industry specialization at sector level on payroll growth. Considering specialization at NHO level, the results indicate a positive impact on payroll growth. However, the effect appears only in the second sub-period. We also find support for the findings from part B and C, indicating a NHO threshold value of 40%. We draw this conclusion, as the *Preferred NHO30* variable is not statistically significant for any period.

Table 5.3.10: Payroll growth - Year 1-5

VARIABLES	(1) Payroll Growth	(2) Payroll Growth	(3) Payroll Growth	(4) Payroll Growth
Preferred Sector50	-0.818			
	(0.556)			
Preferred NHO50		0.822		
		(0.500)		
Preferred NHO40			0.632	
			(0.499)	
Preferred NHO30				0.0567
				(0.494)
Joint Ventures	-1.333	-1.154	-1.136	-1.263
	(0.950)	(0.906)	(0.924)	(0.947)
Nr. Investment VC	-0.0484	-0.0250	-0.0368	-0.0429
	(0.0480)	(0.0514)	(0.0504)	(0.0490)
Years Since Foundation	-0.247***	-0.240***	-0.241***	-0.246***
	(0.0721)	(0.0740)	(0.0743)	(0.0739)
Years Since Foundation^2	0.00483***	0.00454***	0.00466***	0.00494***
	(0.00161)	(0.00171)	(0.00172)	(0.00172)
Patents Year 1	-3.70e-05	-4.73e-05	-4.88e-05	-3.95e-05
	(0.000116)	(0.000102)	(0.000105)	(0.000109)
Financial Bust	0.381	0.607	0.569	0.458
	(0.599)	(0.598)	(0.602)	(0.589)
Financial Bust Performance	-0.372	-0.191	-0.217	-0.330
	(0.673)	(0.674)	(0.680)	(0.701)
Offshore & Shipping	1.623	2.057*	2.024*	1.840*
	(1.047)	(1.039)	(1.049)	(1.054)
Telecom, IT & Tech	0.0470	-0.382	-0.412	-0.305
	(0.732)	(0.734)	(0.738)	(0.696)
Electricity	3.085***	3.516***	3.459***	3.277***
	(0.982)	(0.984)	(0.985)	(1.015)
Wholesale & Retail	-1.425	-1.219	-1.263	-1.370
	(2.289)	(2.231)	(2.234)	(2.257)
Finance	0.0637	0.337	0.262	0.215
	(1.229)	(1.228)	(1.220)	(1.217)
Other Services	-0.454	-0.462	-0.483	-0.536
	(0.670)	(0.712)	(0.711)	(0.683)
Constant	2.983***	2.209**	2.363***	2.687***
	(0.835)	(0.882)	(0.866)	(0.892)
Observations	120	120	120	120
R-squared	0.189	0.187	0.182	0.173

Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport and Construction omitted due to collinearity

Table 5.3.11: Payroll Growth - Year 1-3

VARIABLES	(1) Payroll Growth	(2) Payroll Growth	(3) Payroll Growth	(4) Payroll Growth
Preferred Sector50	-0.591			
	(0.411)			
Preferred NHO50		0.112		
		(0.397)		
Preferred NHO40			-0.137	
			(0.377)	
Preferred NHO30				0.106
				(0.333)
All Control Variables Included	Yes	Yes	Yes	Yes
Constant	2.038***	1.807**	1.955**	1.817**
	(0.697)	(0.785)	(0.763)	(0.747)
Observations	120	120	120	120
R-squared	0.294	0.279	0.279	0.279

Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport omitted due to collinearity

Table 5.3.12: Payroll growth - Year 3-5

VARIABLES	(1) Payroll Growth	(2) Payroll Growth	(3) Payroll Growth	(4) Payroll Growth
Preferred Sector50	-0.338			
	(0.418)			
Preferred NHO50		0.700**		
		(0.335)		
Preferred NHO40			0.741**	
			(0.340)	
Preferred NHO30				-0.116
				(0.390)
All Control Variables Included	Yes	Yes	Yes	Yes
Constant	0.672	0.128	0.144	0.633
	(0.470)	(0.494)	(0.488)	(0.500)
Observations	120	120	120	120
R-squared	0.132	0.149	0.154	0.127

Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport and Construction omitted due to collinearity

E. Productivity Growth

Finally, we seek to evaluate payroll growth and revenue growth in relation to each other, by considering *Productivity Growth* as the dependent variable. Table 5.3.13-5.3.15 depicts the results from the regressions. Examining the results, we are not able to find any results of statistically significance. This holds true irrespectively of the time period. Thus, neither specialization on sector nor NHO level appear to affect productivity growth in PCs. As all the variables are insignificant we cannot determine anything regarding the threshold value.

In total, we conclude that neither specialization on sector nor NHO level affects productivity growth.

Table 5.3.13: Productivity Growth - Year 1-5

VARIABLES	(1) Productivity Growth	(2) Productivity Growth	(3) Productivity Growth	(4) Productivity Growth
Preferred Sector50	-0.0713			
	(0.163)			
Preferred NHO50		0.149		
		(0.164)		
Preferred NHO40			0.192	
			(0.156)	
Preferred NHO30				0.0414
				(0.142)
Joint Ventures	0.00673	0.0332	0.0527	0.0163
	(0.246)	(0.240)	(0.244)	(0.244)
Nr. Investment VC	-0.0236	-0.0197	-0.0210	-0.0224
	(0.0148)	(0.0142)	(0.0143)	(0.0144)
Years Since Foundation	-0.0239	-0.0226	-0.0221	-0.0237
	(0.0190)	(0.0189)	(0.0189)	(0.0190)
Years Since Foundation^2	0.000651	0.000586	0.000572	0.000650
	(0.000397)	(0.000385)	(0.000396)	(0.000398)
Patents Year 1	2.76e-06	1.09e-06	-3.58e-07	2.35e-06
	(1.68e-05)	(1.70e-05)	(1.73e-05)	(1.68e-05)
Financial Bust	-0.249	-0.214	-0.206	-0.235
	(0.164)	(0.168)	(0.161)	(0.159)
Financial Bust Performance	-0.284	-0.254	-0.244	-0.274
	(0.214)	(0.214)	(0.210)	(0.211)
Offshore & Shipping	-0.780**	-0.720*	-0.702*	-0.750*
	(0.378)	(0.376)	(0.380)	(0.380)
Telecom, IT & Tech	0.332*	0.285	0.265	0.290
	(0.192)	(0.191)	(0.186)	(0.185)
Electricity	0.727***	0.789***	0.803***	0.755***
	(0.233)	(0.225)	(0.234)	(0.240)
Wholesale & Retail	0.143	0.177	0.183	0.157
	(0.543)	(0.527)	(0.521)	(0.538)
Finance	-0.158	-0.121	-0.128	-0.136
	(0.281)	(0.272)	(0.273)	(0.279)
Other Services	-0.151	-0.146	-0.144	-0.162
	(0.206)	(0.214)	(0.217)	(0.207)
Constant	0.550***	0.434**	0.418**	0.502**
	(0.189)	(0.196)	(0.199)	(0.197)
Observations	120	120	120	120
R-squared	0.134	0.138	0.143	0.133

Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport and Construction omitted due to collinearity

Table 5.3.14: Productivity Growth - Year 1-3

VARIABLES	(1) Productivity Growth	(2) Productivity Growth	(3) Productivity Growth	(4) Productivity Growth
Preferred Sector50	0.000647 (0.115)			
Preferred NHO50		0.0122 (0.110)		
Preferred NHO40			-0.0308 (0.0986)	
Preferred NHO30				0.0770 (0.0998)
All Control Variables Included	Yes	Yes	Yes	Yes
Constant	0.504*** (0.188)	0.497** (0.198)	0.522*** (0.193)	0.461** (0.194)
Observations	120	120	120	120
R-squared	0.173	0.173	0.173	0.175

Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport omitted due to collinearity

Table 5.3.15: Productivity growth - Year 3-5

VARIABLES	(1) Productivity Growth	(2) Productivity Growth	(3) Productivity Growth	(4) Productivity Growth
Preferred Sector50	-0.0879 (0.165)			
Preferred NHO50		0.112 (0.159)		
Preferred NHO40			0.203 (0.147)	
Preferred NHO30				-0.0607 (0.139)
All Control Variables Included	Yes	Yes	Yes	Yes
Constant	0.162 (0.208)	0.0645 (0.219)	0.0193 (0.217)	0.171 (0.221)
Observations	120	120	120	120
R-squared	0.149	0.151	0.160	0.148

Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
Transport and Construction omitted due to collinearity

Summary and Discussion Part II

The overall aim of this part of the thesis was to analyse how specialization at different industry levels affecting performance in PCs. Based on this we developed the following two sub-questions: i) At what industry level must a VC firm specialize in order to benefit from the positive effects on specialization? ii) Is there a threshold for how specialized a VC firm needs to be within that industry level to benefit from these effects?

Considering the first sub-question, we find no evidence suggesting a positive effect of specialization at sector level on performance in PCs. Moreover, the results provide evidence that specialization at NHO level has a positive effect on the performance of PCs. This relation is found when measuring the effect of specialization at NHO level of both *Revenue Growth* and *Payroll Growth,* as well as on the likelihood of achieving *Increased Revenues* and *Increased Profits*. The effect is positive and statistically significant for the entire period when considering *Revenue Growth*, but only statistically significant in different sub-periods when evaluating the other performance measures. However, in total the evidence point towards a positive effect of VC firm specialization at NHO level on the performance of PCs.

Regarding the second sub-question, we find results suggesting 40% as a threshold value in relation to specialization at NHO level. In other words, in order to exploit the benefits of being specialized at NHO level, it is required that at least 40% of the previous investments undertaken by the VC firm need to be in the same NHO as the NHO of the PC in question. We deduce this as our results in large are pointing towards the *Preferred NHO40* variable affecting performance in PCs and not the *Preferred NHO30* variable. Table 5.3.16 provides an overview of the statistically significant results from part II, when applying a 10% significance level.

Table 5.3.16: Significant results from part II. Applying a 10% significance level

	Increased Profits	Increased Revenues	Revenue Growth	Payroll Growth	Productivity Growth
Preferred Sector50					
Preferred NHO50	$+**_2$	$+**_3$	$+**_1$	$+**_3$	
Preferred NHO40	$+***_2$	$+***_3$	$+**_1$	$+**_3$	
Preferred NHO30	$+**_2$				

+/-=Sign of the coefficient
Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
1=Year 1-5, 2=Year 1-3, 3=Year 3-5

Having outlined the findings from part II, it is appropriate to provide a discussion related to our findings. Sector can unarguably be defined as a broad industry categorization, which captures a variety of different types of companies providing completely dissimilar products or services. One example is the Information and Communication Technologies sector (ICT). The companies being part of the ICT sector require different guidance and support from a VC firm. This makes the sector categorization too large in order for a VC firm or a venture capitalist to acquire what can be viewed as specialized knowledge or competences. This could explain why we do not find any evidence of a positive relationship between specialization at sector level and performance in PCs.

There are 21 different NHO´s. This makes each NHO a much narrower categorization than the sector level, and the NHOs contains companies that are much more similar to each other than companies within a sector. The knowledge and competence acquired in a NHO is likely more specific for the companies being part of the NHO, than what the knowledge and competences acquired in a sector is to the companies being part of the sector. This makes it easier to achieving specialized knowledge or competence for a VC firm or a VC capitalist at NHO level. This may explain why we find a positive relationship between a VC firm investing in their preferred NHO and performance in PCs, and not from investing in their preferred sector. Even though there are 21 different NHOs, each of them do include companies that are dissimilar along some dimensions. This might explain why it requires as much as 40 % of previous investments to be in the same NHO as the NHO of the PC in question, in order to capitalize on the benefits of being specialized at NHO level.

In sum, industry specialization seems to have a positive effect on the performance of PC´s when VC firms specialize at NHO level, and have portfolios with more than 40% of the investments in the same NHO.

Our findings are in line with the findings of Gompers et al. (2009) finding that the performance of specialized firms appear to be better in general. They define specialization as the ratio of all previous investments undertaken by the VC firm in a certain industry, to all previous investments irrespectively of industry.

Until this point, we have found that both the related specialization of a VC firm and industry level specialization at NHO level have positive effect on the performance in PCs. In part III we aim to elaborate these findings further by looking at the two in relation to each other.

5.4 Part III

Research question III: *How does the combined effect of related and industry level specialization of a VC firm affect the performance of portfolio companies?*

In the last part of our analyses we seek to combine insights from part I and II. We do this by creating an interaction term combining the variable *Spec*, used in part I, and *Preferred NHO40*, used in part II. By this, we measure the joint effect of the degree of related specialization and industry level specialization. More precisely, we try to explain whether the effect of the degree of related specialization of a VC firm, is different when a VC firm invest in its preferred NHO or not, on PC performance. For guidance related to how we interpret the variables when including an interaction term, we refer to the methodology section. In part II we discovered that both *Preferred NHO50* and *Preferred NHO40* were positive and statistically significant on performance in PCs. We decide to proceed by using the *Preferred NHO40* variable as our measure for industry level specialization, as this categorization leaves us with more observation within this group than using the *Preferred NHO50* variable. We find this advantageous, because this makes the comparison more robust.

As we only conduct one regression for each performance measure we find it more convenient presenting all the performance measures together. We split the regressions into three parts in order to look at the effects in different periods. The results from the regressions are presented in table 5.4.1-5.4.3.

Starting by using *Increased Profits* as the dependent variable, we find no significant results when considering the entire period. This also applies for the second sub-period. However, examining the results from the first sub period, we discover that the *Preferred NHO40* variable is statistically significant at a 10% level. As the interaction term is not statistically significant within a 10% significance threshold we cannot assign a meaningful economic interpretation to this result.

Next, we use *Increased Revenues* as the dependent variable. We do not find any statistically significant results considering the entire period and the first sub-period. Taking the second sub-period into account we find that the interaction term is significant at 10 % level. This implies that there is a positive relationship between the degree of related specialization within a VC firm and the likelihood for a PC to experience increased revenues in the second sub period, when the VC firm invest in their preferred NHO. Examining the *Spec* variable in the same regression, we find that the opposite is true if the VC firm invests outside their preferred NHO. Put differently, a higher degree of related specialization within a VC firm investing outside their preferred NHO reduces the likelihood for a PCs to achieve increased revenues. This result is significant at a 5 % level.

When using *Revenue Growth* as the dependent variable we find that the interaction term as well as the *Spec* variable is significant. Both these results are statistically significant at a 5% level. Considering the interaction term, this indicates a positive relationship between the degree of related specialization of a VC firm and revenue growth in PCs, when the VC firm investing in their preferred NHO. Contrary, the *Spec* variable indicates a negative relationship between the degree of related specialization within a VC firm and revenue growth in PCs, when a VC firm invests outside their preferred NHO. These results are significant when considering the entire time period. Taking the two other sub periods into consideration, this only holds holds true for the second sub period.

Conducting the regression using *Payroll Growth* as the dependent variable we are not able to identify any significant results when considering the entire period and the first sub-period. However, investigating the second sub-period we find that the coefficient of the interaction term is positive and statistically significant at a 10% level. This indicates a positive relationship between the degree of related specialization within a VC firm and *Payroll Growth* in a PC, when the VC firm invests in their preferred NHO. In this case we find that the *Spec* variable is not significant within a 10 % significance level.

When we conduct the last regression using *Productivity Growth* as the dependent variable, we learn that the interaction term, and the *Spec* variable are both statistically significant at a 10% level when considering the entire period. First, studying the interaction term we find that there is a positive relationship between the degree of related specialization of a VC firm and *Productivity Growth* in PCs, when the VC firm invest in their preferred NHO. Second, analysing the *Spec* variable we learn that there is a negative relationship between the degree of related specialization within a VC firm and productivity growth in PCs, when they invest outside their preferred NHO. Studying the first sub-period we do not find any statistically significant results when applying a 10 % significance threshold. Analysing the second sub-period we find that the *Spec* variable is statistically significant at a 10% level. However, as the interaction term is not significant there is no meaningful economic interpretation of this result.

Table 5.4.1: All Performance Measures. Year 1-5

VARIABLES	(1.logit) Increased Profits[1]	(2.logit) Increased Revenues[2]	(3.OLS) Revenue Growth[3]	(4.OLS) Payroll Growth[4]	(5.OLS) Productivity Growth[5]
Spec	0.250	0.0605	-1.453**	-0.445	-0.192*
	(0.321)	(0.363)	(0.590)	(0.439)	(0.108)
Preferred NHO40	0.444	0.739	-0.596	-0.185	-0.303
	(1.121)	(1.088)	(1.251)	(1.048)	(0.317)
Preferred NHO40#spes	-0.0528	-0.0868	1.638**	0.592	0.323*
	(0.567)	(0.557)	(0.787)	(0.585)	(0.189)
Joint Ventures	-0.746	-0.476	1.556	-0.926	0.137
	(0.653)	(0.689)	(1.301)	(0.858)	(0.247)
Nr. Investment VC	0.0139	-0.0870**	-0.0683	-0.0280	-0.0166
	(0.0472)	(0.0441)	(0.0638)	(0.0519)	(0.0140)
Years Since Foundation	0.124**	0.0313	-0.165**	-0.234***	-0.0179
	(0.0593)	(0.109)	(0.0790)	(0.0742)	(0.0191)
Years Since Foundation^2	-0.00108	-0.00511	0.00313*	0.00458***	0.000543
	(0.00148)	(0.00646)	(0.00163)	(0.00168)	(0.000393)
Patents Year 1	0.000158*	-1.43e-05	1.82e-05	-6.00e-05	-8.31e-06
	(8.85e-05)	(4.80e-05)	(7.64e-05)	(0.000110)	(2.14e-05)
Financial Bust	-0.109	-0.170	0.0640	0.525	-0.231
	(0.484)	(0.477)	(0.617)	(0.612)	(0.162)
Financial Bust Performance	0.824	-0.264	-0.925	-0.283	-0.291
	(0.586)	(0.514)	(0.914)	(0.712)	(0.217)
Offshore & Shipping			-0.0898	2.298**	-0.571
			(1.454)	(0.979)	(0.351)
Telecom, IT & Tech	0.477	-0.413	-0.136	-0.381	0.264
	(0.604)	(0.551)	(0.849)	(0.737)	(0.180)
Electricity			3.694***	3.240***	0.703***
			(1.080)	(1.055)	(0.235)
Wholesale & Retail	0.354	-0.945	0.677	-1.030	0.255
	(0.964)	(1.097)	(2.494)	(2.270)	(0.519)
Finance			-0.140	0.559	0.0127
			(1.424)	(1.296)	(0.277)
Other Services	0.224	-0.459	-0.537	-0.409	-0.118
	(0.583)	(0.597)	(0.888)	(0.696)	(0.215)
Constant	-1.792**	0.983	3.766***	2.759***	0.598**
	(0.743)	(0.782)	(1.043)	(1.009)	(0.235)
Observations	116	116	120	120	120
R-squared			0.216	0.191	0.170
Pseudo R2	0.1173	0.0817			

Pseudo R2: McFadden's Pseudo R2
Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
1) Transport and Construction omitted due to collinearity. Offshore & Shipping, Electricity and Finance omitted due to perfect ability to predict success/failure and 4 observations not used
2) Transport and Construction omitted due to collinearity. Offshore/shipping, Electricity and Finance omitted due to perfect ability to predict success/failure and 4 observations not used
3) Transport and Construction omitted due to collinearity.
4) Transport and Construction omitted due to collinearity

Table 5.4.2. All Performance Measures. Year 1-3

VARIABLES	(1.logit) Increased Profits[1]	(2.logit) Increased Revenues[2]	(3.OLS) Revenue Growth[3]	(4.OLS) Payroll Growth[4]	(5.OLS) Productivity Growth[5]
Spec	0.276	0.402	-0.546	-0.253	-0.0597
	(0.376)	(0.389)	(0.460)	(0.289)	(0.116)
Preferred NHO40	1.578*	0.884	-0.415	0.147	-0.259
	(0.911)	(1.040)	(0.882)	(0.822)	(0.228)
Preferred NHO40#spes	-0.304	-0.513	0.669	-0.0275	0.136
	(0.473)	(0.604)	(0.589)	(0.419)	(0.148)
All Control Variables Included	Yes	Yes	Yes	Yes	Yes
Constant	-2.181***	0.407	1.960*	2.119**	0.575**
	(0.764)	(0.730)	(1.059)	(0.860)	(0.235)
Observations	117	117	120	120	120
R-squared			0.240	0.288	0.179
Pseudo R2	0.1337	0.1045			

Pseudo R2: McFadden's Pseudo R2
Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
1-5) Transport omitted due to collinearity
3) Transport and construction omitted due to collinearity
1-2) Electricity, construction and finance omitted due to perfect ability to predict success/failure, and 3 observations not used

Table 5.4.3. All Performance Measures. Year 3-5

VARIABLES	(1) Increased Profits[1]	(2) Increased Revenues[2]	(3) Revenue Growth[3]	(4) Payroll Growth[4]	(5) Productivity Growth[5]
Spec	0.000841	-0.949**	-1.365**	-0.306	-0.159*
	(0.292)	(0.444)	(0.614)	(0.389)	(0.0887)
Preferred NHO40	0.176	0.106	-0.767	-0.592	-0.131
	(0.981)	(1.073)	(1.130)	(0.602)	(0.264)
Preferred NHO40#spes	-0.0715	1.018*	1.389*	0.777*	0.232
	(0.477)	(0.577)	(0.714)	(0.453)	(0.156)
All Control Variables Included	Yes	Yes	Yes	Yes	Yes
Constant	-0.0833	1.786*	2.265***	0.463	0.164
	(0.731)	(0.978)	(0.846)	(0.526)	(0.229)
Observations	118	118	120	120	120
R-squared			0.229	0.178	0.177
Pseudo R2	0.0488	0.1740			

Pseudo R2: McFadden's Pseudo R2
Robust standard errors in parentheses. Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
1-5) Transport and Construction omitted due to collinearity
1-2) Electricity and Finance omitted due to perfect ability to predict success/failure, and two observations not used.

Summary and Discussion Part III

Part III of the analyses aims at analysing how the combined effect of related and industry level specialization affects the performance in PCs. From the results of the regression models we are able to identify several results of interest. First, higher degrees of related specialization of a VC firm, when investing in their preferred NHO, yields higher performance in the PCs measured by revenue and productivity growth. These results apply for the entire period. Considering the second sub-period this also holds true for the likelihood to achieve increased revenues and payroll growth. We also discover that the effect on revenue growth appears to be more prominent in the second sub-period. Second, higher degree of related specialization within a VC firm, when investing outside their preferred NHO have a negative effect on performance in PCs, measured by revenue growth and productivity growth. This holds true when analysing the entire period. Considering the second sub-period we find similar results when analysing the likelihood for a PC to achieve increased revenues. From the second sub-period we also find that the effect on revenue and productivity growth appears to be more prominent in this sub-period compared to the first sub period. The results of statistically significance, when applying a 10 % significance level, are provided in table 5.4.4.

Table 5.4.4: Significant results from part III. Applying a 10 % significance level

	Increased Profits	Increased Revenues	Revenue Growth	Payroll Growth	Productivity Growth
Spec		$-**_3$	$-**_1, -**_3$		$-*_1, -*_3$
Preferred NHO40	$+*_2$				
Preferred NHO40#Spec		$+*_3$	$+**_1, +*_3$	$+*_3$	$+*_1$

+/-=Sign of the coefficient
Significance levels denoted as: *** p<0.01, ** p<0.05, * p<0.1
1=Year 1-5, 2=Year 1-3, 3=Year 3-5

By including the interaction term, we are able to investigate the effect of having a high degree of industry specialization dependent on whether the VC firm invest in their preferred NHO or not. The results from part III suggest that the degree of industry specialization of a VC firm has a positive effect on the performance in PCs when the VC firm invests in their preferred NHO, and a negative effect if the VC firm invest outside their preferred NHO. This finding is consistent across a variety of performance measures.

The results can strengthen our insights about the mechanisms affecting the relationship between industry specialization of VC firms and performance in PCs. We find that industry specialization has a negative impact on PC performance when the PC is in a different industry than the VC´s preferred industry. This supports the theory of Montgomery and Wernerfelt (1988) describing how specific factors yields lower rents than less specific factors when applied far away from the industry in which they originated. This reasoning explain why the degree of related specialization has a negative effect on the performance of PCs, if the VC firm invest outside their preferred NHO. In this scenario, the VC firm may possess a set of specialized resources originating from a given NHO, that are not applicable to other NHOs. This could for example be specialized knowledge related to a specific NHO, in which is dissimilar to the knowledge required in a different NHO. When a specialized VC firm invests outside their preferred NHO, they have less use of the industry specific resources they possess than when investing in their preferred industry. The result does not only provide evidence that this leads to a diminishing ability to capitalize on the specialized resources, it also shows that industry specific resources have a negative effect on performance when applied in industries far from their origin.

If a VC firm is specialized within a particular NHO, one could reason that this VC firm has managed to acquire specialized resources such as networks and knowledge, related to this NHO. This may add value to the PCs, as the VC firm will be able to provide insights, knowledge and experience in which would otherwise been costly to acquire for the PC. When investing in a preferred NHO, one may reason that a higher degree of related specialization within a VC firm leads to a superior ability to exploit and transfer the value of the resources mentioned above to the PCs. Resultantly, when VCs with higher degree of related specialization invest in their preferred NHO, they improve their ability to add value to the PCs within this NHO.

Summarizing part III, we find that there is a positive effect from industry specialization if the specialized resources and insights are used in the same NHO in which they have originated. Contrary, we find that the similar effect is negative if the resources are used outside the NHO in which they are originated. This supports the view of Wernerfelt and Montgomery (1988) that argue that specialized resources has higher rents in the industry where they originated than in other industries.

6. Concluding Remarks

This master thesis has sought to answer the three following research questions; i) *How does the related specialization of a Venture Capital firm affect the performance of* portfolio companies? ii) *How does a Venture Capital firms′ specialization at a given industry level affect the performance of portfolio companies? iii) How does the combined effect of related and industry level specialization of a VC firm affect the performance of portfolio companies?*

In this final chapter, we will answer these questions and relate the findings. We will also discuss the limitations of the thesis and suggest areas for future research.

In part I of the analysis our aim was to answer how the related specialization of a VC firm affects the performance of PCs. We found evidence which infer that the related specialization of a VC firm has a positive effect on PC performance when measured by i) the likelihood for a PC to achieve increased profits, ii) the likelihood to achieve increased revenues and iii) payroll growth. Moreover, in the latter case, the results suggest a U-shaped relation. We find that the related specialization of a VC firm has a negative effect on PC performance when measured by productivity growth. In part I, we did not find sufficient evidence to conclude that related specialization within a VC firm affects the performance of portfolio companies measured by revenue growth. In the former case this is in contrast to the findings which suggests a positive relationship between related specialization within a VC firm, and likelihood for a PC to achieve increased revenues. This emphasizes that revenues as a performance measure is sensitive to the choice of measurement specification.

Part II of the analysis aimed to answer i) whether VC firm specialization at a given industry level affect the performance of portfolio companies, and ii) if there exists a threshold for how many percent of a VC firm’s portfolio that need to be within the same industry level as the PC in question, in order to exploit the benefits of industry specialization. Based on the result from the second part of the analysis, we found no evidence which infers a positive effect of specialization at sector level. However, we found evidence suggesting that specialization at NHO level has a positive effect on performance in PCs when measured by revenues growth. Examining the sub-periods, we discovered evidence that specialization at NHO level has a positive effect on performance in PCs measured by i) the likelihood for a PC to achieve increased profits, ii) the likelihood for a PC to achieve increased revenues and iii) payroll growth. We found no evidence of any effect between industry-level specialization and productivity growth in PCs.

We found proof suggesting that it requires 40% of the previous investments by the VC firm to be in the same NHO as the NHO of the PC in question, in order to exploit the benefits related to industry specialization. In the case of increased revenues, we found that it only requires 30%.

Part III of the analysis sought to answer how the combined effect of related and industry level specialization of a VC firm, affects the performance of PCs. From the results we were able to identify two main findings. First, the results suggested that a higher degree of related specialization within a VC firm, when investing in their preferred NHO, yields higher performance in the PCs measured by i) revenue growth and ii) productivity growth, when considering the entire period. Considering the different sub-periods this also holds true for ii) the likelihood for a PC to achieve increased revenues and ii) payroll growth. Second, higher degree of related specialization within a VC firm, when investing outside their preferred NHO has a negative effect on performance in PCs, measured by i) revenue growth and ii) productivity growth, when analysing the entire period. Considering the second sub-period this also applies for the likelihood for a PC to achieve increased revenues.

Combining all the findings from the different research questions we provide the following concussion to this master thesis;

First, we find evidence suggesting a positive relationship between industry specialization in a VC firm and the performance of PCs. Second, industry specialization seems to have a positive effect on the performance of PCs when VC firms specialize at NHO level, and have portfolios with 40% or more of the investments in the same NHO as the PC invested in. Third, we find that there is a positive effect from industry specialization if the VC invest in their preferred NHO, and a negative effect of industry specialization when the VC invest outside their preferred NHO.

As with all other studies, ours is subjected to some limitations. As described in the methodology section, there are various ways to measure company performance. Among the PCs that we studied, there exist multiple differences. These could be differences in product, market or growth strategies and stage of the PC in the lifecycle. Given these differences, among the PC firms, we would argue that there is no perfect single measure for PC performance in the short run. We believe that the chosen measures of performance are relevant, but there are unarguably different performance measures that could have been used given more time, data and information related to the PCs.

We can not be perfectly sure that the effects on PC performance that we identify are the result of industry specialization. It is possible that we have a problem with endogeneity, i.e. that an omitted variable influence both the measures of industry specialization and PC performance. An obvious candidate being responsible for the omitted variable bias, is industry experience. One may argue that industry experience to a large degree will influence performance directly, as well as influence the aspects thought to explain the superior performance of specialists. These aspects are among others information advantages, in-depth knowledge and the quality of networks. Most importantly, one may argue that specialization and industry experience is two sides of the same coin when assessing specialization scores based on historic data. A VC firm specializing in one industry over time will per se accumulate industry experience. We control for general experience, measured as the number of investments until the time of the investment in question. We argue that this control variable will capture some of the effect on performance resulting from industry experience. However, this endogeneity problem might still influence our results.

The technique we used when constructing the measures of related specialization has previously been applied by using the SIC code hierarchy. As we use the NACE classification we depend on quite strong assumptions regarding the NACE code hierarchy of industry levels and at what industry levels specialization influence performance. When constructing these variables, we assume that the distances between all industry categories, at the same industry level, are equal and the level differences among all hierarchies of industry levels are equal. Further, we have inflated the level differences of the value weighting factor d_{ij}. These are all assumptions in which is not necessarily perfectly applicable to the real world. Thus, they may violate the measures ability to capture the effects we seek to measure. The measures of related specialization only cover industry specialization. However, a VC firm can be viewed as specialized along this dimension, while at the same time be considered as a generalist along a different dimension, for instance stage or task. Theses types of specialization measures have been accounted for in this study.

The explanatory variables applied in this study are all based on the assumption that specialization can be measured by examining previous investments. However, it is not difficult to find examples that contradict this assumption. For instance, a VC firm might hire General

Partners or employees with specialized expertise related to an industry in which the VC firm historically has not been involved in. In this case, it would be misleading to state that the VC firm has a low degree of specialization in that particular industry solely based on their investment history. The same applies if the VC firm lose GPs or employees with specialized expertise. Further, we calculate the explanatory variables based on all previous investments up until the time of investment. This is similar to the approach used by Gompers, Kovner and Lerner (2009). As employees may join and exit a VC firm, this may cause the structure of the VC firm to not perfectly reflect the related specialization in the VC firm. In order to control for this, we could have based the variables on the investment history covering the last five years. We have not done this, as the calculated scores would have been based on a too few number of observations.

We have been provided with a myriad of accounting information related to PCs. However, there are aspects related to the PCs in which we have not been able to control for due to the lack of information and ability to observe. For instance, information related to alliances, network and details related to the human capital of the PC. We also have limited information concerning VC firms and details related to the transactions. One example is missing information on the amount invested in a PC by a VC firm, as a fraction of the total amount invested by a VC firm, in a given time period. If we had been able to control for such aspects, it would have improved the ability to isolate causality.

Lastly, we should emphasize the fact that our study is based on a somewhat small data sample. This may raise some concerns related to extreme values. However, we seek to account for this by constructing the performance measures the way we do. A small data sample also implies that the explanatory variables are calculated based on a low number of observations.

Several avenues for future research can originate from this study. Analysing other performance measures is one example. If more detailed information concerning PCs were available, it would have been interesting to design other performance measures in which are more suited to capture performance in different types of PC. This can capture performance aspects that are not apprehended in this study. Further, it could have been interesting to use other measures of industry specialization in a VC firm. The study could be extended to not only consider industry specialization at VC firm level, but also venture capitalist level. In the extension of this, it would have been interesting to analyse how different human capital compositions in a VC firm, for instance, the mix of specialized and generalised venture capitalists, affect performance in PCs. Finally, a better understanding of whether the superior performance in PCs backed by VC firms with industry specialization is due to these VC firm's abilities to better select promising PC, or if these VC firms are better to add value to the PC, would have been fruitful.

Appendix

Table A1: Dependent Variables – Correlation Matrix

	Increased Profits Y1-5	Increased Profits Y1-3	Increased Profits Y3-5	Increased Revenues Y1-5	Increased Revenues Y1-3	Increased Revenues Y3-5	Revenue Growth Y1-5	Revenue Growth Y1-3	Revenue Growth Y3-5	Payroll Growth Y1-5	Payroll Growth Y1-3	Payroll Growth Y3-5	Productivity Growth Y1-5	Productivity Growth Y1-3	Productivity Growth Y1-3
Increased Profits Y1-5	1														
Increased Profits Y1-3	0,3320	1													
Increased Profits Y3-5	0,5996	-0,0691	1												
Increased Revenues Y1-5	0,3320	0,0960	0,2652	1											
Increased Revenues Y1-3	0,1727	0,1101	0,1054	0,4809	1										
Increased Revenues Y3-5	0,2001	-0,0334	0,2335	0,5011	0,0000	1									
Revenue Growth Y1-5	0,0572	-0,0282	0,1475	0,3492	0,0821	0,4070	1								
Revenue Growth Y1-3	0,0015	-0,0941	0,0763	0,1432	0,342	-0,0446	0,5784	1							
Revenue Growth Y3-5	0,0656	0,0584	0,0986	0,2700	-0,2362	0,5201	0,6096	-0,2941	1						
Payroll Growth Y1-5	-0,2792	-0,0230	-0,1685	0,1703	0,1129	0,1451	0,5183	0,2863	0,3291	1					
Payroll Growth Y1-3	-0,2872	-0,1431	-0,0725	-0,0538	0,0743	-0,0474	0,3023	0,3458	0,0181	0,7385	1				
Payroll Growth Y3-5	-0,1155	0,1144	-0,1742	0,3079	0,0901	0,2641	0,4540	0,0652	0,4685	0,7148	0,0563	1			
Productivity Growth Y1-5	0,3249	0,1441	0,3066	0,3534	0,1713	0,2885	0,6314	0,3561	0,3937	0,2437	0,1429	0,2126	1		
Productivity Growth Y1-3	0,1461	0,1447	0,0586	0,1021	0,3479	-0,1061	0,3447	0,5940	-0,1735	0,1263	0,1661	0,0148	0,4391	1	
Productivity Growth Y1-3	0,2077	0,0245	0,2632	0,2741	-0,1199	0,3843	0,3523	-0,1399	0,5487	0,1416	0,0050	0,2045	0,6485	-0,3991	1

Table A2: Explanatory Variables – Correlation Matrix

	Spec	Spec^2	Mostspecialized	Match	Match^2	Bestmatch	Preferred Sector 50	Preferred NHO50
Spec	1.0000							
Spec^2	0.9340	1.0000						
Mostspecialized	0.7919	0.6449	1.0000					
Match	0.6875	0.6775	0.4816	1.0000				
Match^2	0.7002	0.7796	0.4376	0.9264	1.0000			
Bestmatch	0.4966	0.3925	0.4000	0.7589	0.5517	1.0000		
Preferred Sector 50	0.4401	0.3733	0.3585	0.6653	0.5410	0.6658	1.0000	
Preferred NHO50	0.3693	0.3569	0.2508	0.4903	0.3947	0.5374	0.3713	1.0000
Preferred NHO40	0.4147	0.3721	0.3271	0.5932	0.4749	0.6369	0.4717	0.8788
Preferred NHO30	0.4021	0.3401	0.2834	0.6943	0.5158	0.7834	0.5768	0.6922
Joint Venture	0.1835	0.1890	0.3107	0.0038	0.0961	-0.1195	-0.0812	-0.1224
Nr. Investment VC	-0.0563	-0.1809	-0.1017	0.0049	-0.1071	0.1517	-0.0254	-0.2017
Years Since Foundation	-0.1040	-0.0738	-0.2299	-0.0773	-0.0780	-0.0377	-0.0994	0.1012
Years Since Foundation^2	-0.0956	-0.0797	-0.1741	-0.0570	-0.0723	0.0176	-0.1176	0.1353
Patents Year 1	0.2112	0.3439	0.0644	0.1910	0.3437	-0.0041	-0.0271	0.0368
Financial Bust	-0.0626	-0.0854	-0.0183	-0.0275	-0.0554	0.0183	-0.0266	-0.1609
Financial Bust Performance	0.1004	0.1893	0.0952	-0.0043	0.1065	-0.2094	-0.0055	-0.0744

	Preferred NHO40	Preferred NHO30	Joint Venture	Nr. Investment VC	Years Since Foundation	Years Since Foundation^2	Patents Year 1	Financial Bust	Financial Bust Performance
Spec									
Spec^2									
Mostspecialized									
Match									
Match^2									
Bestmatch									
Preferred Sector 50									
Preferred NHO50									
Preferred NHO40	1.0000								
Preferred NHO30	0.7876	1.0000							
Joint Venture	-0.1666	-0.1127	1.0000						
Nr. Investment VC	-0.0806	-0.1052	-0.0292	1.0000					
Years Since Foundation	0.0855	0.0653	-0.0992	0.1223	1.0000				
Years Since Foundation^2	0.1160	0.0758	-0.0789	0.1404	0.8567	1.0000			
Patents Year 1	0.0448	0.0077	0.1567	-0.1361	0.0276	-0.0106	1.0000		
Financial Bust	-0.1183	-0.1177	-0.0504	0.1670	-0.0311	-0.0345	0.0353	1.0000	
Financial Bust Performance	-0.1032	-0.0854	0.1970	-0.1806	-0.0812	-0.0880	0.1107	-0.3787	1.0000

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