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Venture Capital Time-to-Exit

An empirical study of Norwegian venture capital divestments and holding periods

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Abstract

Using a dataset comprising of 505 venture capital deals conducted in Norway between 1993 and 2012, this thesis examines the rate of successfully divesting portfolio companies and the corresponding holding period. By manually combing through every deal and determining entry date, exit date and exit type, we find the duration for a majority of the investments. Exit type is then binomially classified as either success or failure based on the category of exit.

The framework of survival analysis is used to estimate the survival functions of the investments and provide unbiased, descriptive statistics on the investments and their time-to-event, categorized as any successful exit. A competing risks analysis examines the effects of a number of covariates in terms of investment sector, fund type and investment stage.

The analyses find significant differences between corporate venture capital funds and independent venture capital funds, with the corporate funds showing a tendency to hold their investments for a longer time span and having fewer successful exits. We further find a significantly lower incidence of successful exit among investments done at the seed stage and investments done in companies operating in the cleantech-sector.

The results are tested by conducting a logistic regression. When including fixed fund effects, we find the statistical significance to deteriorate in some of the findings, but the general conclusions do not change.

The findings have interesting implications for both investors and entrepreneurs in the venture landscape, and could provide a platform from which further research is conducted.

Preface

This thesis was written as a part of our Master of Science in Finance at the Norwegian School of Economics.

Writing a thesis on venture capital has been challenging both with regards to the unique economic mechanisms at play within the subject and the large challenges in gathering data. Nonetheless, the work has been exceedingly rewarding and allowed us insight into a field of which we both have a profound interest.

We would like to express our sincerest gratitude to our supervisor, Associate Professor Kyong Hun (Kyle) Lee, for his continued support throughout the writing process. Knowing his door was always open helped us immensely when we were facing obstacles (which could be quite often).

We would also like to thank Associate Professor Carsten Gero Bienz and the Argentum Centre for Private Equity for assisting us with the procurement of the data on which this thesis is built.

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Contents

1. Introduction

Actively managed portfolio companies generated a total value of 37.2 billion NOK in 2016, representing 1.6% of Norwegian mainland GDP and employing nearly 70 000 people (NVCA, 2017a). Nearly half of these companies were owned by seed - and venture funds, thus constituting the largest growth potential. It could very well be that the next “unicorn” is a Norwegian start-up currently seeking funding, or already in a venture capital portfolio waiting to bloom, which is why it is important to have insight into the characteristics of the investment cycle and its outcomes.

The successes and failures of new ventures are in large part determined by their early access to capital, necessitating a well-functioning private capital market to fuel innovative businesses and commercialize new technology. Venture capitalists play a vital role in nurturing start-ups when access to other forms of financing is limited, by providing growth capital and guidance in exchange for a stake in the company. The symbiosis of the entrepreneur and the risk financier is thus a paramount interaction in any productive economy.

There are large risks involved when conducting venture investments, with low success rates and illiquid positions dictating the need to “make it big” when successfully divesting a portfolio company. The complicated process of developing a new venture with a successful exit in mind can be time-consuming, and there are a multitude of factors which affect both the likelihood of successful exit and the holding periods involved. This thesis will attempt to shed some light on the subject by providing insight into the length of the investment cycle of Norwegian venture capitalists investing in Norwegian portfolio companies by looking for differences with regards to sector, stage and fund type.

We study time to exit for successful and failed investment outcomes from the venture capitalist’s point of view. Our goal is to illuminate the different factors that may explain how long a venture capitalist is involved in a portfolio company and how this may affect the likelihood of successfully exiting.

Our empirical analyses are based on a dataset received from the Argentum Centre for Private Equity, providing a sample of Nordic private equity deals made between 1982 and 2012. We filter out all non-venture investments as well as non-Norwegian venture capitalist funds and portfolio companies and are left with a sample of 505 venture deals. Our data includes information on stage and sector for all deals, but is mostly lacking in terms of entry date, exit date and exit type. We therefore spend a considerable amount of time collecting the necessary information on each individual deal and are successful in complementing around ¾ of the data with complete holding periods and exit information.

Our empirical work can be split into two parts. First, we use the method of survival analysis to estimate survival and hazard functions of different forms of venture investments. Survival analysis is well suited for our dataset as it enables us to use observations without full holding periods. In doing so we are able to include still active investments and investments missing exit dates, thus lessening the bias we would have had, had we not included them in the analyses.

Secondly, we use logistic regression with successful exits as the predicted variable, estimating a number of factors though to affect the likelihood of successful exit. In using two different empirical approaches we are able to provide a robust analysis of the outcomes of Norwegian venture investments.

The thesis is structured as follows:

- Part 2 provides a theoretical background for our analysis, introducing relevant literature on the subject and detailing our specific research interests for the thesis.
- Part 3 describes the data, the process of gathering extra information, and the variables included in the final set.
- Part 4 provides descriptive statistics of the dataset
- In part 5 we conduct a series of survival analyses, using both a non-parametric and a semi-parametric model to illustrate the exit outcomes as a function of months-to-exit.
- In part 6 we use a logistic regression to determine if the data follows the same trends as found in part 5.
- In part 7 we summarize our results, deliver concluding remarks and discuss weaknesses in the analyses, before providing suggestions for further research.

2. Theory

In the following section we will provide definitions on private equity, venture capital and corporate venture capital, review literature relevant to the thesis, and discuss factors thought to influence the length of the investment cycle and exits. Lastly, we discuss our main interests for the thesis and formulate three specific research questions.

2.1 Private Equity

Private equity (PE), as defined by the European Venture Capital Association, is "*the provision of equity capital by financial investors - over the medium or long term – to non-quoted companies with high growth potential"* (EVCA, 2007).

Private equity thus mainly differs from public equity in that it refers to investments in companies which cannot be traded on a public exchange. This entails that PE investments are illiquid and difficult to value. Furthermore, PE generally involves active ownership, with the investor involved in monitoring and assisting the portfolio company (PC). Disregarding participation in shareholders meetings, investors in public companies do not have the same degree of control over their investments. Active ownership can result in additional value added besides the capital itself as investors contribute with industry expertise and networks. This process takes time, and the holding periods are therefore generally longer than with traditional investments in stocks and bonds.

PE funds are typically structured as a limited partnership with the investors acting as the limited partner (LP) and the firm managing the fund acting as the general partner (GP).

2.2 Venture Capital

Venture capital (VC) is a subset of private equity which generally applies to entrepreneurial undertakings rather than mature businesses and refers to investments made to launch or accelerate early development and expansion of a business (EVCA, 2007).

Metrick and Yasuda (2010) define 5 main characteristics of venture capital funds:

1. A VC is a financial intermediary, investing its investors' capital directly into portfolio companies
2. A VC invests only in private companies – those not listed on a public exchange
3. A VC takes an active role in monitoring and helping portfolio companies
4. A VC's primary goal is to maximize its financial return by exiting its investments through a sale or an Initial Public Offering (IPO)
5. A VC invests to fund the internal growth of companies

Characteristic (1) is important as it separates VCs from angel investors, who use their own capital and therefore do not function as a financial intermediary. When investing one's own money, the cost of capital will generally be lower as all the returns are kept by the investors, and there is therefore a difference in the economic dynamics compared to VC investing. Angel investors are thus often able to invest in deals unavailable to VCs.

VC funds are, like other PE funds, structured as a limited partnership. The venture capitalist, or GP, raises capital from a number of LPs which is then invested through the fund into a portfolio of companies. The limited partners remain limited due to their lack of involvement in the investment decisions of the fund.

Characteristic (2) entails that VC investments are illiquid and difficult to value accurately. As we shall discuss further, this means that the timing and type of exit is of paramount importance for the VC, and planning for it is an essential part of the due diligence process. The illiquidity of investments in private companies also has a profound effect on the holding periods, which are, as we will see later on, subject to a number of factors.

The means through which VCs monitor and help their portfolio companies usually takes place through at least one position on the board of directors. This gives the VC an opportunity to oversee their investment and separates them from a passive investor. In taking an active role in the portfolio company a VC is adding value besides capital, and their returns will not only be contingent upon the ability to choose the right opportunities, but also how they take part in the business development. Moreover, VCs often possess deep industry knowledge and a wide network which can be highly valuable to young ventures. In taking on the role of an active owner the VC is able to reduce the operational risk associated with the PC. This oversight is a defining characteristic of VC investing, and believed to be a source of competitive advantage for VC-owned companies compared to others (Sorensen, 2007).

Characteristic (4) defines the preferred types of exit for a VC investor. As the PCs usually do not generate positive cashflows in the early stage, and the focus in general is on growing the business, the VC cannot expect any dividends. Thus, the only means through which the fund may gather a return on its investment is through a profitable exit. This characteristic further differentiates VC investing from strategic investments done by large corporations. A VC has a clear goal, with a given time horizon and preferred exit designed to maximize the financial returns, whereas a corporate investor can have other, strategic motives for buying into a company. The need for a planned exit is therefore not as strongly present, and the strategic investor will behave differently from the VC.

An amalgation of the two, which we will discuss in detail later, is *corporate venture capital (CVC)* funds. These are venture arms of corporations that operate as traditional VC funds but may also have the parent’s strategic goals in mind when making investment decisions in addition to purely financial motives.

Lastly, characteristic (5) summarizes the main function of a VC: to help companies grow organically. The means through which this is achieved is, as mentioned, both through the supply of capital and active participation in staking out the companies’ future course.

The VC investment cycle incorporates the process of the investment from screening and deciding on a deal to exiting its position in the portfolio company. To simplify, we roughly divide the investment cycle in 3 parts; pre-deal, pre-exit and exit. For the purposes of this thesis we are mostly interested in the exit stage and its relation to the length of the investment cycle.

A VC may choose to invest in a number of different company stages, which can roughly be divided in the following (Metrick & Yasuda, 2010); seed stage, early stage, mid stage and later stage. For the purpose of this thesis we mostly differentiate between the seed stage, which is a company at the preliminary stages of proving concept, and the rest, which we simply refer to as the venture stage. There are intuitive differences in risk between the two, and, as will be discussed later, intrinsic differences in both the likelihood of success and the duration of the investments.

VCs prefer to invest in companies with substantial technological risk and high upside potential (Ghosh & Nanda, 2010). As the technological risk is not resolved before significant investments have been made in the PC, large amounts may have been invested before a project is written off. To compensate for this, VCs spread the risk over several investments in a portfolio of companies, and the investments that do succeed make up for the losses incurred by the others. As many investments are generally made to dispense the technology risk over several investments, VCs further prefer to invest in companies with low capital intensity (Kerr & Nanda, 2010). The preference for technological risk and upside potential combined with low capital demands make sectors such as information and communications technology ideal for the purposes of VC investing. Companies in this sector often commercialize quickly, allowing for a shorter holding period before exit. On the other end of the spectrum are companies that require large initial investments to gain commercial viability, such as those needing to build manufacturing plants or scale up a prototype technology. If the potential PC demands too large an initial investment relative to the capital available to the VC, it will generally not be chosen.

As downside protection against the high risk of the companies in which they do invest, VCs often demand convertible shares, thus hedging some of the risk while still being able to participate in the upside should the investment succeed (Gompers & Lerner, 2004). By staging their investments and extend the financing of a PC conditional upon it reaching earlier defined “milestones”, the VC only supports those companies continuing to show promise of success.

VC funds are structured to have a lifespan of about 10 years (Ghosh & Nanda, 2010), and are typically compensated in the form of a management fee of around 2% of committed capital as well as carried interest at around 20% of excess return. Gompers and Lerner (2004) theorize that VCs prefer to exit their investments well before the 10-year mark. In doing so, they can establish a track record of successful exits beneficial to raising new funds. Thus, one might infer that younger VCs without a proven track record are more likely to exit their investments early. Gompers (1996) further provides evidence for his theory of *grandstanding* in the VC industry, in which young VCs, in an effort to establish their reputation, take PCs public earlier than incumbent, senior funds. Individual VC characteristics are thereby likely to affect the exit decision.

There exists a variety of exit options for VCs, the most common being (Cummings & MacIntosh, 2000):

- IPO exit, in which the PC’s shares are sold to the public market

- acquisition exit, in which the PC is sold to a third party
- a secondary sale, in which the VC's shares are sold to a third party
- a buyback, in which the VC's shares are sold back to the PC
- write-offs, in which the PC is liquidated at no profit for the VC

All of these exits entail a different set of factors thought to affect the holding period of the investment.

Cummings and MacIntosh (2000) examine the relationship between investment duration and exit strategy of a sample of venture capital investments in the USA and Canada, finding a number of factors to be of statistical significance on the holding period of the investments. Most notable among these is a significant difference with regards to the stage of firm at first investment. The earlier the investment is in the PC lifespan, the riskier it is. However, given that more equity can be attained for a lower price in the seed stage, the upside potential is generally much higher.

Cumming and Johan (2010) further suggest that VCs exit when the expected marginal cost of maintaining the investment exceeds the expected marginal benefit, and formulate a number of factors related to PC and VC characteristics as well as market conditions impacting this.

2.3 Corporate Venture Capital

Corporate Venture Capital (CVC) is the systematic practice by established corporations of making equity investments in entrepreneurial ventures (Drover et al., 2017). CVC funds mostly invest in emerging, innovative companies with technologies that are strategically aligned with the parent firm (Ernst et al., 2005). This form of corporate investing originated in the US in the 1960s and has been rapidly increasing in the last decades. Now large corporations in nearly all sectors are establishing CVC units (EY, 2018).

In many ways, CVC funds share similarities with Independent Venture Capital (IVC) funds. However, as discussed in detail by Chemmanur et al. (2014), there are some structural differences which may have an effect on investment activity and exits.

CVCs are stand-alone subsidiaries of non-financial corporations who invest in new ventures on behalf of the parent (Chemmanur et al., 2014). They generally operate as evergreen funds, as the lack of traditional LPs leads to an initially unlimited time-horizon on investments. The structure of a limited partnership limits an IVCs lifespan, and it is unable to invest more than the capital initially committed by its LPs. CVCs do not have such constraints, leaving them free to pursue investment opportunities with a longer time to fruition. Contrarily, Rajan et al. (2000) argue that as CVCs are subject to centralized resource allocation, they are not as free to invest at will as their IVC counterparts.

CVCs further differ from IVCs in their compensation schemes (Dushnitsky & Shapira, 2007). As opposed to IVCs traditional, incentive-aligning system of carried interest and a management fee, CVCs managerial compensation is generally a fixed salary and corporate bonuses tied to parent performance. This lack of purely performance driven compensation may lead to CVCs being more open to experimentation and exhibit a higher failure tolerance, thereby lowering their rate of successful exits.

It might also be theorized that by tying CVCs compensation to that of the parent company, the best interests of the PC are not always considered. CVCs may be incentivized to advance the interests of the parent at the expense of the PC and often invest with a strategic goal in mind, as opposed to the purely financial motives of their IVC counterparts. While CVC also strive to earn returns, the primary owner of a CVC is another company. The parent does not rely on earnings made from the fund to persist in the long run, and consequently the management of a CVC does not necessarily face the same pressure to deliver high financial returns (Gompers & Lerner, 2000). There are often commonalities between the chosen PCs and the sectors in which the parent's main area of business resides. Consequently, the parent company provides a potential exit for CVC PCs, and may choose to liquidate the investment early if there is a strategic fit of the PCs intellectual assets or business model.

2.4 Research Questions

As we have seen, there is an abundance of factors discussed in the literature thought to influence both the choice of exit and the holding periods of VC investments. Naturally, the scope of this thesis as well as the data available prevents us from examining them all. We therefore restrict our analysis to focus on a select number of factors thought to influence holding periods and exits. To do so, we use a dataset comprising of Norwegian deals from 1993-2012, which we intend to use to present an analysis of the Norwegian VC market. In our analyses we are interested in providing an empirical discussion on investment lengths of failed and successful investments as well as differences between sectors, investment stages and fund structure.

We have formulated three research questions illustrating our main interests in the topic.

Research question I

Is there a difference in holding periods and the rate of successful exits between CVCs and IVCs in the Norwegian market?

Based on the previously discussed nature of CVC investments, we hypothesize a lower rate of successful exits and longer holding periods for CVC compared to IVC.

Research question II

Are there significant differences between sectors?

We wish to provide a descriptive analysis of the Norwegian VC market, detailing which sectors represent the largest part of VC investments. Furthermore, we wish to examine if there are statistical differences in holding periods and outcomes between sectors.

Research question III

Are there significant differences between investment stages?

We hypothesize that seed investments are riskier than later stage VC deals, and as such expect a lower rate of successful exits.

3. Data

The empirical work presented in this thesis is based on a dataset received from the Argentum Centre for Private Equity. We received two datasets containing information on Nordic PE deals ranging from 1982-2012 and 2013-2016 respectively. As the primary interest of this thesis is to look at investment outcomes, we ignored the latter dataset owing to the fact that most of these investments were still active. In this section we describe the sample available to us and detail the process of gathering information to supplement the dataset.

3.1 Initial Demands for Dataset

Our primary concern when analysing venture deals has been biased results due to the nature of PE-reporting, which tends to underreport failed investments and highlight successful exits (Scott, 1994).

When complementing the dataset with holding periods, finding entry and exit dates on successful investments proved significantly easier than finding the equivalent information on failures. As such, efforts would need to be made to ensure we did not allow for survivorship bias by finding disproportionally more information on successful investments. Secondly, as we were interested in comparing IVC and CVC investments, we needed to correctly identify and isolate CVC investments. To be able to test for significant differences between the two it would be necessary to have a large enough sample size of CVC investments. Thirdly, we would need information on entry and exit times as well as exit type for a majority of the data. When no information on exit was available, we would need to find the latest date we knew the VC to hold a position.

3.2 Filtering of Data

1. *Removing other PE-investments*

Our interest is in VC deals, and as such we removed all investments marked as buyout, leaving only those classified as seed or venture. Our earliest observation is then from 1993.

2. *Removing investments by non-Norwegian VCs*

All non-Norwegian VCs were removed from the dataset, as we wanted the focus to be on the Norwegian market. We define Norwegian VCs as firms headquartered in Norway.

3. *Removing investments in non-Norwegian PCs.*

All investments in companies headquartered outside of Norway were removed from the dataset. This made the data gathering process as described in section 3.3 easier and we do not complicate the subsequent analyses with factors relating to foreign investment. We are thus left with investments made by Norwegian VCs in Norwegian PCs

4. *Removing investments missing vital information and duplicates*

Some observations lacked crucial information such as name of PC or VC, which limited our ability to find their outcomes and holding period lengths. These investments were removed from the dataset. Some investments were also recorded more than once to account for several rounds of financing. In these cases, only the first round of investment was included in the final dataset.

Table 3.1 shows each step of the filtering process.

Initial number of observations	**4818**
Removing non-VC deals	-2957
Removing non-Norwegian funds	-1068
Removing investments in non-Norwegian portfolio companies	-264
Removing investments with unnamed VC or PC and duplicates	-24
Remaining number of observations	**505**

Table 3.1 *– The filtering process*

3.3 Gathering Data

The dataset was lacking in terms of information about investment lengths. 227 observations included entry date, and only 82 observations had a recorded exit date. 92 observations included exit type. Thus, information on entry- and exit date as well as exit type would have to be manually collected for a majority of the dataset, mostly through open sources.

The main source of information has been Venturexpert[1], which is a useful tool for gathering entry dates in particular, as it in many cases provides detailed information about investment rounds in PCs. When Venturexpert yielded no results, the missing information could in some cases be found using databases such as CrunchBase[2] and Pitchbook[3]. However, these sources proved inadequate in providing detailed information on failed investments.

Gathering exit data on failed investments proved challenging due to the previously discussed issues of underreporting failed investments amongst VCs. The webpages of VCs often display the active investments in their portfolio and only a select number of successful exits. Following the logic that failed investments would be deleted from the list of active PCs and not included among selected exits, we used the online internet archive *Wayback Machine*[4] to find the last date an investment was displayed on the VCs homepage. An approximate exit time could then be deduced by taking the median date between last known active date and first known non-active date.

The same logic was applied to other open sources, such as online newspapers and annual company reports. As such, we were able to gather approximate exit dates on a number of failed investments. In other cases, we were only able to record the last date we knew the VC to have been active. This still conveys valuable information for the survival analyses that will be conducted in part IV and was consequently included in the dataset as *last active as of.*

Many companies that have received VC funding and failed to develop to a successful exit continue to operate as dormant companies, typically only employing one or two people and generating low to no turnover. In these cases, the logic that VCs often take board positions was followed, and consequently the last date a VC held a position on the board was used as the write-off time.

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[1] VentureXpert is a database providing comprehensive information about private equity deals. We were able to access it through NHH's subscription to SDC Platinum.

[2] CrunchBase is a platform providing information on investment rounds and funding amounts

[3] PitchBook is a database providing data on the private capital market

[4] Wayback machine is a digital archive of the internet, allowing the user to access webpages as they looked on selected historical dates

For some investments, the VC appeared active until the PC was liquidated. Liquidation dates as recorded on *www.Proff.no*[5] was then recorded as the exit date.

3.4 Potential Bias

We identify two main sources of potential bias in the dataset; survivorship bias and sample bias.

3.4.1 Survivorship Bias

Survivorship bias arises when one overlooks observations that have not survived a given selection process. In looking at the performance of a portfolio of companies that includes only surviving companies, we risk survival bias (Rohleder et al., 2010).

The difficulty in finding information on failed investments involves a potential for survivorship bias in the completed dataset. After supplementing the investment lengths as detailed in section 3.3, 128 observations had incomplete holding periods due to no information on either entry, exit or both. As will be discussed later, the burden of proof lies with the successful exits, and we can safely assume a majority of these investments to be failed ones. Not including them in the following analyses would result in misleading estimates of success rates and holding periods, and we intend to control for this issue by using survival analysis.

3.4.2 Sample Bias

The original dataset had the potential for sample bias if certain types of investments were overrepresented relative to others. This thesis is based on the assumption of the ACPE providing an unbiased sample of VC deals, thus precluding any particular sample bias from being prevalent. Upon looking at the activity of the funds in the dataset in the time period, we found some investments which were not included amongst the observations. Given this, we cannot conclude that the dataset contains *all* Norwegian VC investments conducted in the time period. However, assuming no particular trend in the omitted observations, we proceed with our analysis unconcerned with sample bias in the dataset.

[5] www.Proff.no is a database of accounting information, investors, board positions and more for Norwegian companies

3.5 Definition of Variables

3.5.1 Investment Outcomes

To allow for the use of dummy variables of success in our analyses, we differentiate between successful exits and failures. For the purpose of further studies, we would have preferred data on returns in order to measure relative degrees of success, but as finding this proved inexpedient the dataset was limited to binomial outcomes. We aspired to have a conservative measure on successful divestments. Thus, emphasis was placed upon the burden of proof lying with proving success, and all non-active investments in which no exit type was determined were classified as failures.

The distinction between failure and success can be problematic to define clearly. In some cases, an exit is made which isolated could be regarded as successful. The question is where to draw the line. Is a failure only an investment in which the VC does not get back their capital? If we define failures only as those cases where the PC was liquidated at a complete loss for the VCs, we would get an excessively low failure rate, whereas if failure is defined as any investment which does not meet the VCs projected investment return we would get an excessively high failure rate.

It is important to bear in mind the characteristics of VC investment; long holding periods; illiquid positions; the nature of VC compensation and large risks all imply the need for high returns on the investments that do succeed. Based on this we formulate a definition of success to use as a benchmark to assess investment outcomes:

We define a successful divestment as any form of profitable exit which would be sustainable for the VC in the long run.

We generalize the investment outcomes as success or failure by taking this definition into account. As we do not have information on specific investment returns, we cannot conclude with certainty that each investment is classified correctly as a failure or success. For example, a trade sale could become a loss for the VC by returning less than the original investment. Concurrently, an acquisition exit at a multiple of 2 of the invested amount for a holding period in excess of ten years can hardly be called very successful. Still, investment outcomes are classified as successes or failures based on the general sustainability of the outcome itself. In the completed dataset we are then left with the following outcomes:

1. *IPO*

An IPO, or initial public offering, is the process through which a private company is made public by an initial share offer (Ritter & Welch, 2002). An IPO is one of two generally preferred exit strategies for a VC, the other being M&A (Metric & Yasuda, 2010). When a company is made public, the shares must still be sold on the market and it is not a given that a VC sells its entire position, but we still choose to treat any IPO in the dataset as a successful exit for the VC for the purposes of analysis. Exit dates are thus determined as the date of the IPO, and is easily found through open sources.

2. *M&A*

Mergers and acquisitions also represent a successful exit for the VC through the complete sale of its position. The most common form of M&A exit for VCs in our dataset is by *trade sale*, a simple acquisition in which the entire company is purchased by another. Exit dates for M&A are typically easily accessible on the previously mentioned databases.

3. *Share sale*

We have some observations of investments where a VCs position has been successfully exited through a share sale. This might be to another fund, to the management of the PC (a buyback) or to private investors. Share sales are characterized as successful exits.

4. *Secondary market sales*

The forms of secondary sales we have discovered in the dataset have been funds selling off their entire portfolios to other funds. After assessing each secondary sale individually, and bearing our definition of successful exits in mind, the secondary sales are classified as failures[6].

5. *Write-offs*

Written off investments are investments that do not succeed, most of which have either been liquidated or continue to operate as dormant companies, generating low to no turnovers and with only one or two employees. Write-offs are classified as failed investments.

[6] One can hardly argue that a sustainable form of VC investing would rely on building a portfolio only to sell it off in its entirety. We theorize that the cases we have seen have been due to closing down a fund with bad performance, resulting in positions being acquired for “cents on the dollar”.

6. *Still active*

For the investments in which no exit has occurred, we set the date of exit as *still active as of 01.06.2018,* as we cannot be certain that all sources are recently updated. As the burden of proof lies with proving success, *still active* investments are initially classified as failures. We do not have an outcome and thus cannot determine if these investments will be successful or not, and our interest is in their *known holding periods* for the purpose of the survival analyses in part 5. However, dormant companies in which the VC still holds a position are classified as write-offs.

7. *No info*

We searched extensively in order to deduce the holding periods and exit types of all investments in the dataset, but for around a quarter of the dataset we were not successful at finding one or both. It is safe to assume that nearly all of these are failed investments, and as the burden of proof lies with the successful exits, these are marked as failures.

Our findings are summarized in table 3.2.

Success	Obs.	%	Failure	Obs.	%
Share sale	26	5.1	No info	128	25.3
IPO	12	2.4	Secondary	10	2
Trade sale	125	24.8	Still active	99	19.6
Merger	10	2	Write off	92	18.2
MBO	3	0.6			
Total	176	34.9	Total	329	65.1

***Table 3.2** – Exit outcomes in dataset*

3.5.2 Months-To-Exit

We use investment and exit dates to generate a variable for the holding periods of each investment expressed in months.

3.5.3 CVC

We screened all funds to determine which were CVC funds, and included a dummy variable for each observation detailing if the investment was made by a CVC fund or not. Our definition of a CVC fund is any fund working as a corporate subsidiary of a non-financial corporation. In total, we found 5 funds that could be classified as CVC funds, representing 84 investments.

3.5.4 Fund Activity

To allow a measure of VC scope, a variable was added for each investment containing the number of other investments the given VC has in the dataset. A spread of risk through more investments tends to make the VCs less risk averse (Forbes, 2009), and we would therefore expect VCs with a high number of investments to have a lower success rate.

3.5.5 Sector

The ACPE dataset had seven sector categories for the investments; *cleantech*[7], *consumer*[8], *energy*[9], *ICT*[10], *industrial*[11], *life science*[12] and *other*[13]. We included these classifications in the final set and formulated dummy variables for each sector.

3.5.6 Seed

The ACPE dataset differentiated between seed and venture when classifying investment stage. We are interested in determining if there are differences between seed investments and other venture investments, and therefore included a dummy variable for seed.

VCs often invest in multiple rounds of financing, with new investors coming in at various stages. Ideally, our analyses would account for this through a variable detailing at which investment round the VC entered. However, we found that collecting information on this was not feasible, and thus only differentiate between seed and venture. Investments

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[7] *Cleantech* is a sector comprising of companies devoted to clean technology: most notably recycling, electric motors and renewable energy such as wind energy, solar energy, biofuels etc.

[8] *Consumer* is a sector comprising of companies devoted to serving the market of consumer goods

[9] *Energy* is a sector comprising of companies in the energy industry, most notably petroleum, gas, and electrical power

[10] *ICT* is a sector comprising of companies in the industry of information and communications technology

[11] The *industria*l sector is the secondary sector of the economy, and can be interpreted as industries manufacturing finished and semi-finished goods from raw materials

[12] *Life science* is a sector comprising of companies in the fields of biotechnology and pharmaceuticals

[13] *Other* is a term for all companies that cannot be accurately described as belonging to any of the aforementioned sectors

classified as venture will consequently account for all investment rounds that are not seed financing.

4. Descriptive Statistics

In the following section we present a summary of our completed dataset. Tables 4.1-4.3 present descriptive statistics on all deals, IVC deals and CVC deals.

Table 4.1 *All VC Deals*
This table presents descriptive statistics of all observations in the dataset. Success rates are included in parenthesis for each respective sector, stage and fund type. Fund activity represents the number of investments within each fund. As we were not able to determine the duration of all investments, total success rates including and excluding no info deals is added. Months-to-exit is calculated using all observations with complete holding periods, all successes with complete holding periods and all failures with complete holding periods.

Variable	Obs	Mean	Std.Dev.	Min	Max
Cleantech (17,2%)	505	.127	.333	0	1
Consumer (26,1%)	505	.046	.209	0	1
Energy (39,1%)	505	.137	.344	0	1
ICT (46,6%)	505	.378	.485	0	1
Industrial (21,4%)	505	.083	.276	0	1
Lifescience (24,3%)	505	.147	.354	0	1
Other (40,5%)	505	.083	.276	0	1
Seed (34,1%)	505	.366	.482	0	1
Venture (37,8%)	505	.634	.482	0	1
Fund activity	505	21.505	11.561	1	45
IVC (38,2%)	505	.834	.373	0	1
CVC (17,9%)	505	.166	.373	0	1
Failure	505	.651	.477	0	1
Success w/noinfo	505	.349	.477	0	1
Success wo/noinfo	377	.467	.5	0	1
Monthstoexit - all	377	80.339	41.436	6	228
Monthstoexit-success	176	69.661	41.137	6	210
Monthstoexit - failure	201	89.345	39.832	10	228

Table 4.2 *IVC Deals*
This table presents descriptive statistics on IVC deals in the dataset. Success and failure rates are calculated including no info deals. Months-to-exit is calculated using all observations with complete holding periods, all successes and all failures.

Variable	Obs	Mean	Std.Dev.	Min	Max
Cleantech	421	.124	.329	0	1
Consumer	421	.048	.213	0	1
Energy	421	.138	.345	0	1
ICT	421	.363	.482	0	1
Industrial	421	.074	.261	0	1
Lifescience	421	.166	.373	0	1
Other	421	.088	.283	0	1
Seed	421	.418	.494	0	1
Venture	421	.582	.494	0	1
Fund activity	421	19.834	9.386	1	32
Failure	421	.618	.487	0	1
Success	421	.382	.487	0	1
Monthstoexit - all	322	79.817	42.592	6	228
Monthstoexit-success	161	68.359	41.300	6	210
Monthstoexit-failure	260	91.274	40.861	12	228

Table 4.3 *CVC Deals*
This table presents descriptive statistics on CVC deals in the dataset.
Success and failure rates are calculated including no info deals. Months-to-exit is calculated using all observations with complete holding periods, all successes and all failures.

Variable	Obs	Mean	Std.Dev.	Min	Max
Cleantech	84	.143	.352	0	1
Consumer	84	.036	.187	0	1
Energy	84	.131	.339	0	1
ICT	84	.452	.501	0	1
Industrial	84	.131	.339	0	1
Lifescience	84	.048	.214	0	1
Other	84	.06	.238	0	1
Seed	84	.107	.311	0	1
Venture	84	.893	.311	0	1
Fund activity	84	29.881	16.754	5	45
Failure	84	.821	.385	0	1
Success	84	.179	.385	0	1
Monthstoexit - all	55	82.139	35.287	10	209
Monthstoexit-success	15	83.633	37.821	24	142
Monthstoexit-failure	40	81.580	34.777	10	209

4.1 Fund type

We identify only five CVC funds in the data, representing a total number of 84 investments. The low number of CVC funds is surprising, but we must bear in mind the time period of our dataset, and, as discussed in part 2, the rising trend of CVC internationally. Although more individual CVCs would have been preferred, we conclude that the relatively high number of investments proves sufficient for empirical analyses.

To check the prevalence of CVC funds in Norway today, we went through *Kapital's* list of Norway's largest companies[14]. Among the 200 largest companies we identified 33[15] that had launched corporate venture programs, with a clear majority having been initiated after 2012. These findings are indicative of the fact that CVC programs are gaining popularity in Norway as well as internationally.

4.2 Success Rate

We observe a general success rate of around 35% when including no-info deals. This result must be interpreted with our definition of failure, as discussed in section 3, in mind. We can be certain that a written off investment is a failure but cannot necessarily conclude that a trade sale or share sale should be classified as successful. Consequently, we infer that *at least* 65% of the investments in our dataset resulted in failures.

The opaque definitions of failure and success in other studies means we should be careful when comparing our results with these. Research from the U.S. market between 2000-2010 indicate that only about 25% return their investors capital (Ghosh, quoted in Gage, 2012), and the U.S. National Venture Capital Association estimate that 25-30% fail completely (Gage, 2012).

Our findings are more in line with Kräussl & Krause (2014), who also use a binomial measure of success and failure. They find a general success rate of 33% for European VC

[14] Each year, the Norwegian financial newspaper *Kapital* compiles a list of Norway's 500 largest companies. The list is accessible at www.kapital.no/norges-500-storste.

[15] 16 of these were CVC divisions headquartered outside of Norway as the parent company was international.

investments in the same time period when using IPO, M&A, and buyouts as measures of successful exits.

We further observe that IVC investments have a success rate of 38% compared to CVCs with 18%. This is in line with the hypothesis we developed in research question I, stating that IVCs would have more successful exits.

4.3 Months-to-exit

When calculating months-to-exit, investments that did not have both an entry and exit date had to be excluded. In doing so, 128 observations were removed. We should therefore not place too much emphasis on months-to-exit for failed investments, as this does not represent the whole sample of failed investments.

We observe that the investments have a total average holding period of 80 months, or 6 years and 8 months. Additionally, we note a high standard deviation suggesting that the durations are spread out over a long range of values. The investment with the shortest duration in our dataset lasted only 6 months, whereas the longest lasted 19 years. Months-to-exit for all successful investments is around 70 months, or 5 years and 10 months. This implies that the average length a VC holds a portfolio company before successfully divesting is nearly 6 years.

For IVCs this figure is nearly the same, at 68 months. The CVCs in the data seem to hold their successful investments longer, divesting on average after 7 years.

4.4 Sectors

We notice, not surprisingly, that *ICT* has the largest share of the investments, with 38% of all deals, followed by *lifescience*, *energy* and *cleantech*. These findings follow the general trends of European VC investing (OECD, 2017; Statista, 2019), although *energy* appears more prevalent amongst Norwegian VC investors. The Norwegian economy’s dependence on oil and gas and the innate competency on the area that this entails may be an intuitive explanation for this. The findings also seem to show the same trend as the Norwegian Venture Capital and Private Equity Association find in their activity report for 2017 (NVCA, 2017b), suggesting that there have not been dramatic changes in the composition of sectors invested in in the last years.

ICT is also the most successful sector, with a success rate of 47%, followed by *other, energy* and *consumer*. The least successful sector is cleantech, with a success rate of 17%.

4.5 Stage

37% of the observations in the dataset were seed investments, the rest were in venture. We note that seed investments are somewhat less successful than venture investments, with success rates of 34% and 38% respectively. This supports our hypothesis as formulated in research question III, that seed investments yield fewer successful exits. Although we would have expected a larger gap, the empirical analyses will have to determine if this is a significant difference.

Surprisingly, only 11% of CVC investments were done at the seed stage, as opposed to 42% of IVC investments. This is interesting when considering the low rate of CVC success compared to IVC. Should our hypothesis from research question III be correct then we cannot attribute the higher success rates among IVC investments to preferences in PC stage. In fact, these preferences should lower the success rates for IVCs.

4.6 Fund Activity

The average number of investments per VC in our dataset is 22. For IVCs it is 20 and for CVCs it is 30. Although we note that CVCs have a higher number of investments, we refrain from drawing any conclusions based on this as we only have 5 CVC funds in our dataset.

5. Survival analysis

In this section we use the framework of *survival analysis* to study holding periods and their relation to successful VC exits. We conduct two forms of analyses; a non-parametric approach and a semi-parametric approach. First, the Kaplan-Meier estimator is used to present unbiased descriptive statistics of the data, estimating the survival functions and differences in these between IVC and CVC investments. Following this, a multivariate, competing risks model is used to account for mutually exclusive events and look for differences in the hazard of exit amongst different types of investments.

5.1 General Model

Survival analysis involves the modelling of *time-to-event* data. It can be defined as a set of methods for analysing data where the outcome variable is the time until the occurrence of an event of interest (Kleinbaum & Klein, 2010). Its traditional use has been in medical research, were the event of interest has been patient death. However, by treating an investment as the "patient" and the successful exit of that investment as "death", we can use the same framework to find the *hazard* – and *survival functions* of VC investments.

The survival function is the probability that a subject survives longer than the given time period by not undergoing an *event.* Contrarily, the *hazard function* gives us the probability that the event will occur at a given time, conditional on the event not having taken place up until that time. In our analysis, the hazard function thereby expresses the probability of successful exit for an investment at any time, given that no successful exit has previously occurred. For the purpose of this analysis, the event is any successful divestment.

5.1.1 Censoring Observations

Survival analysis involves following subjects until either the event occurs or the period of monitoring ends. Even if we do not observe the event happening, the subject still contributes valuable information as we know the minimum length of survival. This happens through *censored* observations.

In our dataset we mostly face the issue of right-censored observations. These are subjects with incomplete survival times due to a loss to follow up or the event in question not occurring. The data contains several missing observations complicating analysis. Many of the investments are still active, and as such we cannot determine if they are successful or not. There are also observations with no exit date, but that we know to be failed investments. These are included in the analyses up to the last point of follow up, which, if we have no other information, is set as one year after investment date. This allows us to include these observations in our analyses as a minimum holding period, and the remaining time is censored. We cannot know what happened to these investments but, seeing as how we were not able to locate an exit date, in most cases it is safe to assume that these are failures. However, by marking them as still active as of one year after investment date, a minimum holding period is included in the analysis before censoring. This lessens the bias in our analysis compared to if we were to exclude them all together. Investments that are still active are marked as still active as of 01.06.2018. 15 observations are excluded due to no entry or exit date.

5.2 A Non-Parametric Analysis

First, a non-parametric approach is applied, meaning no assumptions are made concerning the shape of the parameters in the underlying data. We use it to present unbiased descriptive statistics of the data by censoring observations without complete holding periods and estimating the survival functions.

5.2.1 The Kaplan-Meier Estimator

The Kaplan-Meier estimator (Kaplan & Meier, 1958) is a non-parametric approach to estimate survival functions, which, without the censored observations, would simply present the empirical distribution of the data.

The model is based on a univariate method of analysis and is therefore limited in its ability to estimate survival adjusted for covariates, though effective when comparing survival rates of two groups. We thus use it initially as a new source of descriptive statistics, detailing the survival functions of all investments and to look for differences between IVC and CVC.

We classify *successful exit* as the event, and use holding periods in months as the survival time, called *months-to-exit.* As such, in the following analysis, survival reflects failed investments, those not resulting in a successful exit for our given time period.

The estimator of the survival function is given by

$$\widehat{S}(t) = \prod_{i:\ t_i \le t} \left(1 - \frac{d_i}{n_i}\right), \tag{5.1}$$

where n_i is the number of observations that are still at risk but have not yet undergone an event at time t_i, and d_i is the number of events at time t_i. The function is a continuous product of the conditional probabilities at time t_i, given that the event occurred before t_i.

To simplify, the survival probability can be expressed as the number of divestments at a given time divided by the number of investments at risk of divesting. Investments at risk are not counted in the denominator if they are censored at time t_i. The probability of survival is at any point in time the cumulative probability of surviving the preceding time intervals.

5.2.2 Smoothed Hazard Estimate

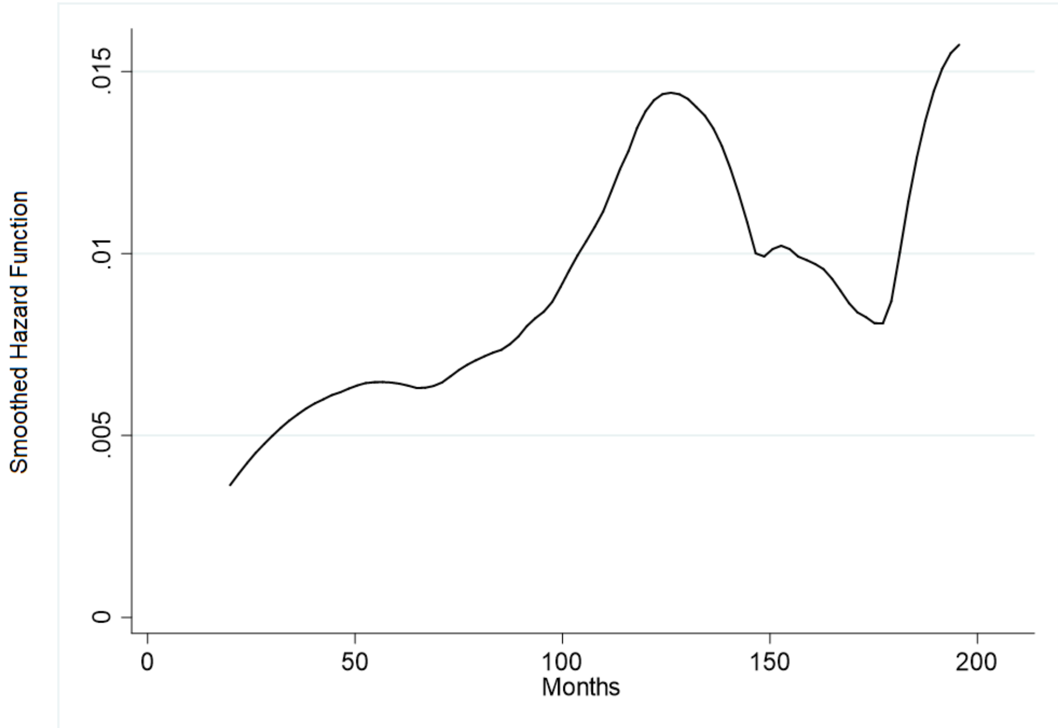

Figure 5.1 - *smoothed hazard estimate*

We begin our analysis with a smoothed hazard estimate as shown in figure 5.1. This curve graphs the hazard function of successful exit for any investment plotted against its duration.

We notice a positive duration dependence, suggesting a rising hazard of successful exit as time passes. Interestingly, after a peak at around 10 years, the hazard drops before rising sharply from 15 years and onward. It must be stressed that we have a very limited number of observations with holding periods of this length, but may infer from the data that the probability of successfully exiting an investment rises steadily til about 10 years. After this divestment becomes less likely.

5.2.3 Kaplan-Meier with all Investments

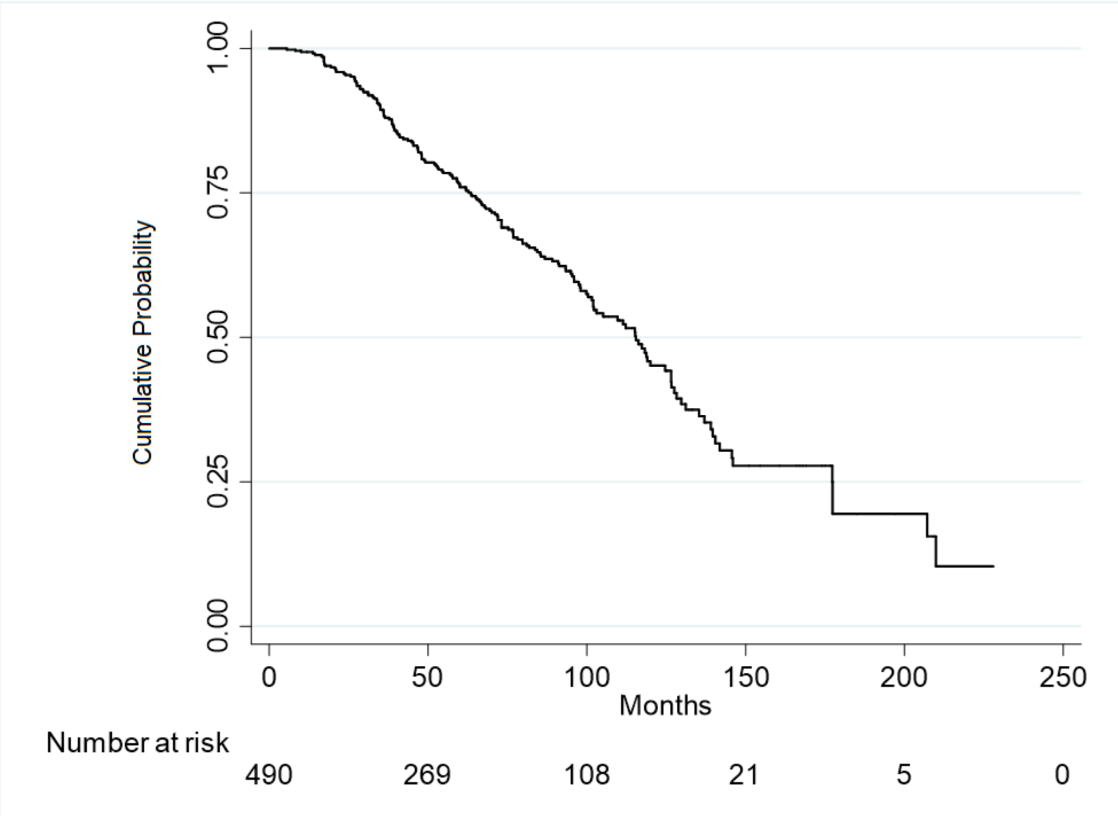

Figure 5.2 *- Kaplan-Meier survival estimate, all investments.*
An event is defined as any successful exit; IPO, M&A and share sale. No-info observations are censored from last known active date. Analysis time is in months, and the number of remaining at risk observations are shown in intervals of 50 months.

The graph in figure 5.2 plots the survival curve of all investments using Kaplan-Meier estimation and defining the event of interest as *successful exit*. An implicit assumption in the graph, which affects our understanding of the data, is that all investments will eventually come to fruition through a successful exit. Consequently, the investments that do not reach the event are censored, and we can see the number of at-risk investments descending as the holding periods increase.

The graph plots the cumulative probability of surviving a given time. It should be emphasized that survival in this case expresses the probability of an investment *not* resulting in a successful exit. The curve gives stepwise estimates of how the cumulative probabilities change between intervals. Each horizontal curve represents an interval in which no exit has occurred. The vertical distance between the horizontal curves illustrate how the cumulative probabilities change with events. As censored investments are not included amongst the number at risk, the high number of censored observations means that these results should be interpreted cautiously.

The median survival time is 115 months. This can be interpreted as 50% of all investments having a duration of at least 115 months, or nearly 10 years.

5.2.4 Kaplan-Meier IVC vs CVC

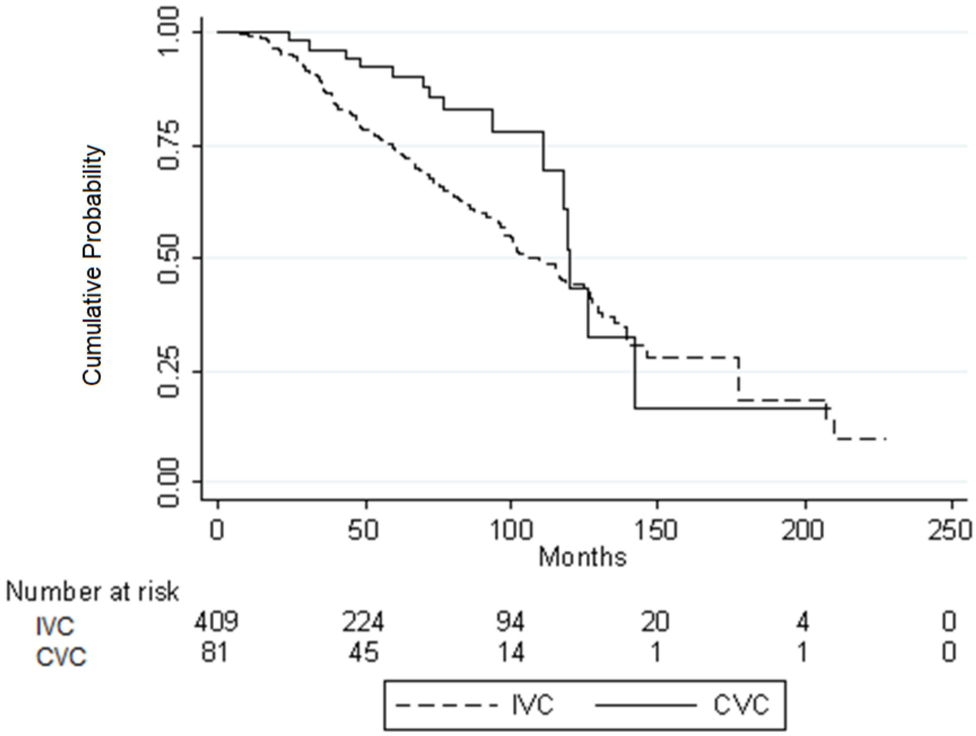

Figure 5.3 *- Kaplan-Meier survival estimate, CVC vs. IVC investments.*
An event is defined as any successful exit; IPO, M&A and share sale. No-info and still-active observations are censored from last known active date. Analysis time is measured in months, and the number of remaining at risk observations are shown for IVC and CVC.

The graph in figure 5.3 compares the survival functions of IVC and CVC investments. We now have two survival functions, plotting the cumulative probabilities of survival against the durations of the investments.

We can graphically discern a trend for CVC investments to initially have a higher survival probability and longer durations, meaning they are less likely to lead to a successful exit and that the ones that do take longer time to come to fruition. After the two curves cross, the number of at-risk observations for CVC are so low that we should be careful with further interpretations.

We are interested in determining if there is a significant difference in the hazard of exit for IVC and CVC. To ascertain this, we test for differences in survival functions using the log-rank test, presented in appendix A.1. We can reject the null hypothesis of equal survival functions at the 5% level. In other words, the probabilities of successful exit differ between the two, and, as we saw from the graph, CVCs have a lower probability of successful exit compared to IVCs.

5.3 A semi-Parametric Analysis

We now use a semi-parametric approach, incorporating the concept of competing risks and the effects of covariates on the data.

5.3.1 The Cox Proportional Hazards Model

The Cox proportional hazards model (Cox, 1972) is a semi-paramateric, multivariate regression analysis allowing us to extend the survival analysis to simultanously assess the effect of multiple factors on survival time. The model examines how different factors influence the event-rate at a specific point in time, called the hazard rate. We refer to these factors as covariates.

The hazard function for subject j is given as

$$h(t|x_j) = h_0(t)\exp(\beta_x x_j), \tag{5.2}$$

where t is the survival time, x_j are covariates and β_j are the coefficients that measure the impact of the covariates. h_0 is referred to as the baseline hazard, which all participants are subject to adjusted for the covariates. Consequently, it reflects the hazard should all covariates be equal to zero. The survival times are not assumed to follow any known distribution, and the shape of the baseline hazard is thus random. This is the non-parametric component of the model.

The hazard ratio is the hazard of one subject divided by the hazard for another. For covariates x_j and x_k the hazard ratio can be expressed as

$$\widehat{HR} = \frac{\hat{h}(t,x_j)}{\hat{h}(t,x_k)} = \frac{\hat{h}_0(t)exp(x_j\beta_x)}{\hat{h}_0(t)exp(x_k\beta_x)}\,. \tag{5.3}$$

Since the baseline hazard is cancelled out, no assumptions are made regarding its shape and a non-linear relationship between the hazard function and the predictor variables is assumed. However, an assumption is made that the hazard ratios are invariant over time. In other words, the effect of a covariant should not change over time when the predictor variables do not change over time. This is known as the *proportional hazards assumption*, and implies that the plotted hazard curves for two groups of observations should be proportional and cannot cross.

We can test for the proportional hazards assumption by determining if the Kaplan-Meier estimated survival functions of two groups cross. In examining the survival curves of figure 5.3, we see that these two curves do indeed cross, indicating that the assumption may be violated. However, given the low number of CVC observations after the curves cross, we conclude that this violation is insignificant for further analysis.

5.3.2 The Fine and Gray Model of Competing Risks

The previous models are based on the understanding of the event in interest ultimately occurring for each subject, even if it happens after the period of observation. The duration between the end of follow-up and event occurrence is consequently censored, as are subjects that drop out of the dataset during the period of observation. However, should these subjects drop out due to an event that obstructs the event of interest from happening, we risk biased estimates.

In other words, a written-off investment cannot lead to a successful exit for the VC, and it should therefore not be censored in the analysis. The Fine and Gray model (Fine & Gray, 1999), treats events that obstruct the event of interest from occurring as competing risks to deal with this issue. It accounts for these risks by treating subjects as still at risk of experiencing the event of interest even though they are no longer able to after having experienced a competing event.

The competing risks model is based on the proportional hazards model, and is also semiparametric with the covariates assumed to be proportional. Although only one event is recorded for each subject, the model gives partial information on all event types. For instance, if an investment is eventually written off, we know that it went a given period of time without a succesful exit before failing.

The competing risk model can then be expressed as an extension of the Cox model:

$$\hat{h}_i(t|x_j) = h_{i,0}(t)\exp(x_j\beta). \tag{5.5}$$

The cause-specific hazard function for cause i, also known as the *subhazard function,* is defined as

$$h_i(t) = \lim_{\delta t \to 0} \frac{\mathrm{P}(t \leq T < t + \delta t, \varepsilon = i | T \geq t \cup (T \leq t \cap \varepsilon \neq i)}{\delta t}. \tag{5.6}$$

This function can be interpreted as the instantaneous risk of cause i occurring at a point in time, given that no event has happened so far (Stata, n.d.). The event observations are expressed as (T, δ), with time-to-event T and δ as a cause indicator, detailing the type of event that occurred.

The cumulative subhazard for event i, $\bar{H}_i$, is given as the integral of the subhazard function from the start of monitoring until t. The *cumulative incidence function* (CIF) can then be expressed as

$$CIF_i(t) = 1 - exp\{-\bar{H}_i(t)\} . \tag{5.7}$$

This function provides the probability of observing the event before a given time when accounting for competing risks.

5.3.3 Competing Risks Analysis

In the following competing risks analysis, dummy variables for success and failure are introduced following the logic that a liquidated investment cannot lead to a successful exit and therefore should not be censored. Investments that are still active are characterized by success = 0 and failure = 0 throughout their lifetime and are promptly right censored after their last known active date.

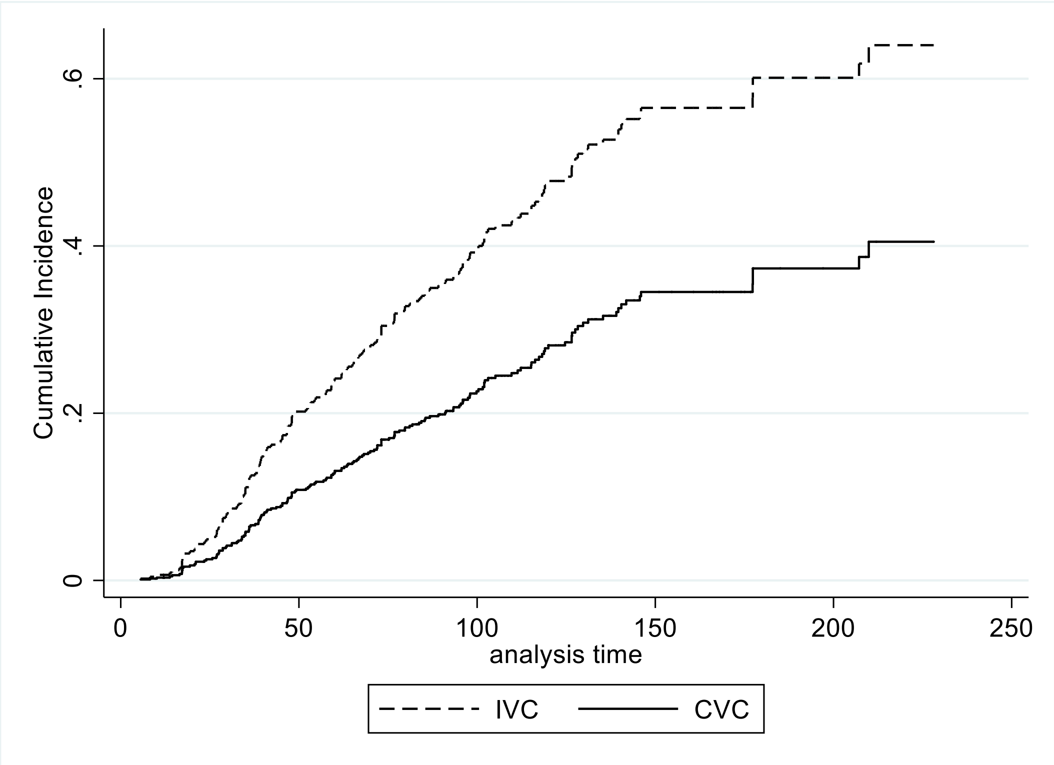

Figure 5.4 *- Cumulative incidence function, CVC vs. IVC.*
The event in interest is any successful exit; IPO, M&A and share sale. Competing events are failed investments; write-offs and secondary sales. No-info and still-active investments are censored from last known active date. Analysis time is measured in months.

Figure 5.4 shows the cumulative incidence function – the probability of exit before a given time in months when accounting for competing events - for IVC and CVC. The graphs are proportional to allow for the proportional hazards' assumption. Once more we discern a trend of lower probability of successful exits for CVC investments. In using the competing risks approach we further notice that in not censoring competing events the graph reflects a lower cumulative probability of successful exit as time passes.

Table 5.2 *- Competing risks regression*
This table presents the subhazard estimates of successful exit; IPO, M&A and share sale. Competing events are any failed investment; write-offs and secondary sales. No-info and still-active investments are censored from last known active date. The dependent variable equals one in the month of a successful exit. CVC is a dummy variable equal to one if the investment is done by a CVC fund. Seed is a dummy variable equal to one if the investment is done in the seed stage of the PC. The sector dummies Cleantech, Consumer, Energy, ICT, Industrial and LifeScience equal one if the investment is done in their respective sector.

	(1)	(2)	(3)	(4)
CVC	0.502**			0.435**
	(-2.69)			(-3.14)
Seed		0.713*		0.697*
		(-2.12)		(-2.11)
Cleantech			0.319**	0.304**
			(-3.01)	(-3.11)
Consumer			0.829	0.865
			(-0.38)	(-0.29)
Energy			0.985	0.882
			(-0.05)	(-0.42)
ICT			1.105	1.048
			(0.42)	(0.19)
Industrial			0.849	0.829
			(-0.44)	(-0.50)
LifeScience			0.522*	0.507
			(-2.02)	(-2.11)
No. of obs.	490	490	490	490
No. of events	176	176	176	176
No. compet.	102	102	102	102
No. censor.	212	212	212	212
P>chisq.	0.007	0.034	0.001	0.000

, ** and * denote statistical significance at the 5, 1 and 0.1 percent level, respectively*
t statistics in parentheses

Table 5.2 presents the results of the competing risks regression where we have introduced dummy variables for covariates of sector, stage and CVC. This allows us to consider the differences from the baseline hazard of these covariates to determine if there are differences in the hazard of successful exits.

The competing risks method shows the estimated coefficients known as subhazard ratios. We can interpret them in the following way: a ratio above one implies that if the dummy covariate equals one, the incidence of exit is raised relative to the baseline hazard, whereas a ratio below one lowers the incidence of exit.

We identify three statistically significant covariates in our regression; CVC, seed and cleantech.

CVC investments are significant at the 1% level at lowering the incidence of successful exit.

This confirms our suspicion based on the plotted cumulative incidence function in figure 4.4 and the results from the Kaplan-Meier estimator, as well as the hypothesis formulated under research question I.

Guo et al. (2015) provide evidence of longer durations for CVC-backed PCs, as well as a general trend for VC investments with a longer duration to have an increased likelihood of acquisition exit. Our findings up to this point are in line with their initial result, as CVCs seem to hold on to investments longer. However, some other mechanism must be at play hindering the success rates of CVCs specifically since these are lower.

It is important to bear in mind that, given our binomial classifications of investment outcomes as successes or failures, this analysis does not present any indication of differences in returns. It could be theorized, based on the literature reviewed in section 2, that the structural differences in CVC funds lead to differences in risk attitude. Following this, CVC funds may gather higher returns on the investments that do succeed. However, there is a strategic component to CVC investing that suggests the differences in success rate may be explained in the motivations behind such investing in the first place.

It is possible that, in strategically acquiring a portfolio company, the parent of the CVC fund chooses to silently incorporate the PC into its business. There are few incentives to disclose such an acquisition (Scott, 1994). In doing so, we would not be able to confirm it as a successful exit, and it would consequently be included as a failure in the data. We theorize that the parent company could provide an exit opportunity for the CVCs portfolio companies for strategic reasons.

One motivation could be to get a foothold in a new market linked to the parent corporation's primary business. A portfolio company with an innovative technology or business plan could provide a platform from which the parent is able to expand to a new market.

Dimitrova (2015) finds that corporate parent companies acquire their CVC units' PCs when the PC shows signs of outperforming the parent in terms of innovativeness. A parent acquisition could thus be linked to declining technological output at the corporation, but also work as a means through which competition is reduced. Dushnitsky & Lenox (2005) suggest that the motivation behind establishing corporate venturing units in the first place is to harvest innovation from new ventures, thereby working to some degree as a substitute for other innovation programs. Empirically, the study shows that an increase in CVC investments is associated with a subsequent increase in firm patenting.

If corporate venturing is used as an initiative to increase R&D output, the success rate would presumably be lower because the primary objective is not to maximize returns.

Seed investments are significant at the 5% level at lowering the incidence of successful exit.

This supports our hypothesis as formulated in research question III; that seed investments would have a lower success rate. There is an intuitive interpretation of this result. Seed investments are, as discussed in section 2, relatively small investments in the very early stage of a company's development. It is generally provided as a means for the entrepreneur to prove a concept and commence the initial process of assembling a team of employees, conducting market research, and developing a business plan. There is therefore an inherently higher risk in providing seed capital as opposed to investing in companies at later stages of development, which we can see reflected in the subhazard ratios. Our results indicate that seed investments have a 30% lower chance of leading to a successful exit relative to the baseline hazard of other investments.

Investments in cleantech are significant at the 1% level at lowering the incidence of successful exit.

The only sector that provides a significant difference in the hazard of exit is cleantech, with a 70% lower chance of leading to a successful exit. A considerable amount of the observations within this sector are in clean energy companies devoted to solar energy, wind energy and biofuel.

A possible explanation for the low hazard of exit within cleantech is the capital-intensive nature of this area of business and the fact that our time period includes the 1990s and early 2000s – a period in which many of the technologies utilized in this sector were in their infancy. Commercializing these technologies at scale can be challenging, and consequently one might infer a higher risk associated with investing in the sector. It could further be postulated that a lack of viable exit opportunities leads to fewer successful divestments within this sector. Ghosh and Nanda (2010) suggest that there is a “bottleneck” in the scaling up process of the clean energy sector in which a lack of incumbent buyers inhibits the VC from handing over the investment once a start-up reaches a juncture of potential acquisition. As the portfolio company develops in capital intensive industries, its infrastructural and managerial requirements increase until it is outside the scope of an entrepreneurial workforce to be handled. Other, similar industries have evolved to the point where incumbent corporations often provide an exit opportunity at this pre-commercial stage, however, energy producing firms are generally reluctant to assist in this regard (Ghosh & Nanda, 2010). As there are fewer exit opportunities at this stage for clean energy companies, the investments take longer to come to fruition and experience lower successful exit rates.

6. Logistic Regression

This section presents the cursory results of a logistic regression conducted as a robustness check to test the results of the previous analyses with a different model. In using a logistic model with a binary dependent variable, we are able to see if our findings indicate the same trends as the survival analyses in section 5.

The weakness of this approach is that, as opposed to in the survival analyses, we are unable to include observations without a complete holding period in the model. The data thus consists of 377 investments. We conduct two regressions with the dummy variable *success* as the dependent variable; one simple regression and one with an added fixed fund effect. Once more we classify investment outcomes as either *successes* or *failures.*

6.1 Model

6.1.1 General Model

Regression analyses are used to examine associations between an outcome and selected independent variables or determine the accuracy of the independent variables to predict an outcome (Wooldridge, 2012). There are different types of regression depending on the research objective and the nature of the variables. Linear regressions are the most commonly used and assumes a linear relationship that follows a straight line between the dependent and independent variables. The success rate of investment *i* is a function of the independent variables affecting that investment:

$$Success\ rate = \propto + \beta_1 * Cleantech + \beta_2 * Consumer + \ldots + \beta_{10} * Monthstoexit + \varepsilon \tag{6.1}$$

where α represents the intercept and β_x represents the slope coefficient: the effect of a one unit increase on the related independent variable.

6.1.2 Logistic Regression

The logistic regression has many similarities to the linear model, but retains the value of the dependent variable to within zero and one. Due to the binary nature of our dependent variable we use logistic regression to predict the relationship between the independent variables, *predictors*, and our dependent, *predicted* variable (Wooldridge, 2012). We are then able to estimate the probabilities of successful exits as a function of the predictors.

The probability of success is given as

$$P(success) = F(\propto + \beta_1 * Cleantech + \beta_2 * Consumer + \ldots + \beta_{10} * Monthstoexit + \varepsilon) \tag{6.2}$$

Which is then transformed using the logistic function

$$P(Success) = \frac{1}{1 + e^{-(\propto + \beta_1 * Cleantech + \beta_2 * Consumer + \ldots + \beta_{10} * Monthstoexit + \varepsilon)}} \tag{6.3}$$

There are several conditions required for the regression to be unbiased and efficient[16]. To validate the model, tests were run for misspecification[17], multicollinearity[18] and heteroscedasticity[19]. We found no misspecification issues in the models, and by excluding *fund activity* in the regressions with fixed fund effect, we removed multicollinearity between the variables. The tests revealed no heteroscedasticity, but robust standard errors were added as a precaution in case of undetected heteroscedasticity.

The model further relies on a random sample. We refer to the discussion in section 3.4 regarding selection bias in the original dataset of 505 observations. However, as 128 observations have been removed, most of which we can assume to be failed investments, there is a certain degree of bias in the following regression. Results must be interpreted with this in mind.

To control for individual fund characteristics and reduce potential omitted variable bias, a fixed fund effect is included. As many years did not have the sufficient number of

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[16] First, the variables in the regression must have a linear relationship. Secondly, the sample must be random. Third, there should be no multicollinearity between all variables. The fourth and final assumption requires the error term to have an expected value of zero given the value of all independent variables. (Wooldridge, 2012). In addition, there must be an absence of heteroscedasticity for the model to be efficient.

[17] We used the Stata command «linktest» in order to detect potential issues of misspecification in the logit model. See appendix A.2.

[18] We used the Stata command “VIF” to detect potential multicollinearity between variables. See appendix A.3.

[19] We conducted a Breusch-Pagan test to detect heteroscedasticity. To reduce potential undetected heteroscedasticity, we included robust standard errors. See appendix A.4.

investments to include fixed years effects, and some investment years created multicollinearity issues, we elected to not include a fixed year effect in the regression.

6.1.2 Dependent Variable

To examine the determinants of success rate, we choose a binomial dependent variable in both regression models. The dependent variable would then yield the probability of success given all included variables representing characteristics of the investment and characteristics of the invested fund.

6.1.3 Independent Variables

In addition to the variables that have been used in the previous analyses, we add a fixed fund effect to control for individual fund characteristics.

The data comprises ranges from VCs conducting only a few investments to those with dozens. To control for fund specific performance differences, a dummy variable equal to 1 if more than 10 investments has been made by the same VC is added. In doing so, 18 fund dummies are added to the model.

6.2 Results

Table 6.1 below presents the results of the regressions.

Positive coefficients indicate an increase in the probability of success by the correspondent independent variable, while negative coefficients indicate a decline in the probability of success by the correspondent independent variable.

If all the dummy variables equal zero the investment is in the *other* sector, the venture stage, or done by an IVC. If all fund dummies equal zero, the investment was made by a fund with less than 10 investments in the dataset.

Table 6.1 *Logistic regression results*

	(1) Logit(Success)		(2) Logit(Success)	
Cleantech	-2.294***	(0.557)	-2.211***	(0.582)
Consumer	-1.001	(0.733)	-1.184	(0.756)
Energy	-0.831	(0.521)	-0.794	(0.568)
ICT	-0.262	(0.480)	-0.441	(0.491)
Industrial	-0.980	(0.637)	-0.663	(0.690)
Lifescience	-1.370**	(0.526)	-1.325*	(0.551)
Seed	-0.510*	(0.257)	-0.369	(0.428)
Fund activity	-0.028*	(0.012)		
CVC	-1.250**	(0.419)	-0.870	(1.008)
Monthstoexit	-0.015***	(0.003)	-0.016***	(0.003)
F1			-1.424	(0.787)
F2			0.110	(0.728)
F3			-2.530*	(1.217)
F4			-1.500**	(0.535)
F5			0.530	(1.170)
F6			-2.485*	(1.130)
F7			0.641	(0.702)
F8			-0.095	(0.569)
F9			-1.105	(0.831)
F10			-0.011	(0.736)
F11			-0.098	(0.635)
F12			-0.108	(0.558)
F13			0.342	(0.625)
F14			-0.602	(0.810)
F15			0.164	(0.767)
F16			-1.091	(0.711)
F17			0.832	(0.973)
F18			1.528	(1.131)
Constant	2.735***	(0.580)	2.565***	(0.654)
N	377		377	
R^2	0.159		0.242	
Misspecification	No		No	
Mean VIF	1.91		1.76	
Heteroskedasticity	Used RSE		Used RSE	

, ** and * denote statistical significance at the 5, 1 and 0.1 percent level, respectively.*
Robust standard errors in parenthesis.
R^2 is a measure of goodness of fit, representing the percentage of sample variation in dependent variables that can be explained by independent variable. No misspecification or multicollinearity issues are present in either regression. Robust standard errors are included to control for potential heteroscedasticity.
CVC is a dummy variable equal to one if the investment is done by a CVC fund. Seed is a dummy variable equal to one if the investment is done in the seed stage of the PC. The sector dummies Cleantech, Consumer, Energy, ICT, Industrial and LifeScience equal one if the investment is done in their respective sector. F1-F18 are fixed fund effects representing funds with more than 10 investments.

The results indicate that *cleantech* and *lifescience* have a negative impact on success rate, at the 0,1% and 5% significance level respectively when including fixed fund effects. This is in line with our findings in section 5, although we did not detect a significant difference in the hazard of exit for lifescience in the competing risks analysis.

Once more it must be stressed that the results should be interpreted with our definition of success in mind. It could be theorized that, although these sectors provide a lower rate of successful exits, the ones that do succeed generate high returns. *Lifescience* involves a number of biotech investments, a sector that, like clean energy, is highly capital intensive and requires large investments in order to commercialize (Ghosh & Nanda, 2010). As these sectors are significant also when including fixed fund effects, the negative effect on success rate cannot be attributed to inferior funds investing in them.

In the regressions, the sector dummy *other*, which is excluded, seems to outperform the other sectors. *Other* incorporates all other investment sectors not specifically defined in our data. As the sectors in the dataset are likely defined based on certain VC preference for investing in them, one could theorize that in investing in companies outside of these sectors, VCs only choose the very best prospects. This could explain why *other* seems to do so well in the data.

Seed is significant at the 5% level at lowering the probability of successful exit when fixed fund effects are not included. This is in line with our findings in section 5. However, when including fixed fund effects, the variable loses its significance. This could indicate that there are intrinsic differences in the funds that conduct seed investments affecting the success rate of this stage.

CVC is also statistically significant in the simple regression, at the 1% level, but loses significance when fixed fund effects are included. This is indicative of characteristics common to CVCs having a negative impact on the success rates, but not necessarily that being a CVC in itself lowers probability of successful exits.

We must once again bear in mind the low number of CVC funds when interpreting the results when fixed fund effects are included.

Fund activity is included in the first regression and is significant at the 5% level at lowering the probability of successful exit. Suggesting that funds that invest in a large number of PCs experience lower success rates.

Months-to-exit is significant at the 0.1% level at lowering the probability of exit. The interpretation of this is, not surprisingly, that the duration of the investment is impactful on the probability of successful exit. The negative impact must be understood in the context of the model. Our findings in section 5 indicate a positive duration dependency when censoring incomplete observations, and is thus more representative of the underlying data.

There are some concerns in the logistic regression conducted in this section, most notably the failure to include all observations and the bias that arises from this. Still, the regressions are meant to be conducted as a robustness check of the general results found in earlier analyses. In doing so, we confirm the general trends of the findings in section 5.

7. Concluding Remarks

7.1 Summary

This thesis has investigated some of the determinants of success rates and holding periods in the Norwegian market for venture capital investments. The main purpose has been to provide a descriptive analysis of the investments themselves and to uncover if there are variations with regards to investment outcome and duration across sectors, stage and fund type. Empirically, the analyses have been conducted through the framework of survival analyses, using both a non-parametric and semi-parametric approach, and then verified against the backdrop of a logistic regression.

Our analyses indicated a significant difference between IVCs and CVCs. CVCs seem to experience fewer successful exits and hold their investments longer on average before divesting. This could be explained by the inherent structural differences between the two types of investors, and we speculate that strategic motives of the parent corporation could explain some of the differences. In addition, we find that some of the variation between the two fund types can be attributed to individual fund characteristics amongst the CVCs.

We have thus found empirical evidence in support of our hypothesis as developed in research question I.

In research question II we wanted to determine if there were significant differences between sectors.

When conducting the survival analysis, we only found one sector with a significantly lower incidence of successful exit, the cleantech sector. We theorize that a possible explanation for this might be the capital-intensive nature of companies operating in this sector and a lack of exit options compared to many other sectors. This result is confirmed in the logistic regression, also when accounting for fixed fund effects. The logistic regression further indicates that lifescience significantly lowers the probability of successful exit, a result we did not find in the competing risks model.

We further found that seed investments experience a lower rate of successful exit than investments done at later stages. This result is not surprising given the intuitively higher risk of investing in a company before much business development has been undertaken. In the logistic regression this result is confirmed, however, when accounting for fixed fund effects we find that the impact of seed investing loses its significance. This could indicate that there is a difference in the funds investing the most in early stages explaining some of the differences.

These findings partially support our hypothesis in research question III. Seed investments seem to experience a lower rate of successful exits, though we cannot be certain if it is the act of investing at this stage itself or the funds that do this form of investments that are the cause.

The results presented in this thesis should be interpreted with our definition of success in mind. In categorizing investments as either successes or failures, a lot of nuances are lost due to not accounting for varying degrees of success. Collecting data on returns for all investments in the dataset proved inexpedient for the scope of this thesis, which was why we rather chose to classify investment outcomes based on the general sustainability of the outcomes themselves.

Although in particular the survival analysis is suited for observations with missing exit dates, we would naturally have preferred full durations for all investments. Missing observations on holding periods is thus a limitation to this thesis. In addition, there are a number of variables thought to influence the success rates and durations that we have not been able to analyse. One of these are macroeconomic conditions, which we would expect to influence the exit decision and duration of the investments. We leave this to future researchers on the topic. Although the number of CVC investments were high, a higher number of CVC funds would have been preferred for the validity of results.

7.2 Suggestions for Further Research

We have complemented the original dataset from the Argentum Centre with complete holding periods on a majority of the VC investments. This provides a platform from which a number of interesting studies could be conducted. A natural starting point would be to further distinguish between different types of exits, for example by looking for differences in the time-to-event for IPOs and trade sales.

Tian and Wang (2011) construct a measure for failure tolerance based on the holding periods and number of investment rounds of failed investments. The willingness to continue investing in underperforming ventures is then linked to a higher degree of innovativeness with the portfolio companies. Replicating this study for the Norwegian market could prove very interesting, especially given the current discussion on how to raise innovativeness in the Norwegian economy.

The discussion of the findings in section 5 further opens up for potential topics to investigate.

We anticipate that as the trend of corporate venturing increases in Norway, more data on exits within this segment will become available. Our main findings concerning the differences between CVCs and IVCs could then be checked using a larger empirical foundation. Furthermore, if statistics were to become available on parent acquisitions in a corporate venture setting, the motivations for such activity could be examined in detail.

As the topic of clean energy becomes ever more relevant, an in-depth analysis of why the rate of successful exit is so low within cleantech would be interesting.

Lastly, it could be interesting to see if the trends uncovered in this thesis are the same across the Nordics, or if there are inherent differences in success rates and holding periods between the countries and when cross-border investing.

We highly encourage future researchers to investigate these topics closer.

References

Chemmanur, T. J., Loutskina, E., & Tian, X. (2014). Corporate venture capital, value creation, and innovation. *The Review of Financial Studies*, *27*(8), 2434-2473.

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society: Series B (Methodological)*, *34*(2), 187-202.

Cumming, D., & Johan, S. (2010). Venture capital investment duration. *Journal of Small Business Management*, *48*(2), 228-257.

Cummings, D. J., & MacIntosh, J. G. (2003). Venture-capital exits in Canada and the United States. *U. Toronto LJ*, *53*, 101.

Dimitrova, L. (2015). Strategic acquisitions by corporate venture capital investors. *Available at SSRN 2553786*.

Drover, W., Busenitz, L., Matusik, S., Townsend, D., Anglin, A., & Dushnitsky, G. (2017). A review and road map of entrepreneurial equity financing research: venture capital, corporate venture capital, angel investment, crowdfunding, and accelerators. *Journal of Management*, *43*(6), 1820-1853.

Dushnitsky, G., & Lenox, M. J. (2005). When do incumbents learn from entrepreneurial ventures?: Corporate venture capital and investing firm innovation rates. *Research Policy*, *34*(5), 615-639.

Dushnitsky, G. Z., & Shapira, Z. (2007). *Entrepreneurial finance meets corporate reality: comparing investment practices by corporate and independent venture capitalists*. Working paper, University of Pennsylvania.

EVCA, T. F. (2007). European Private Equity Performance Benchmarks 2007, March 2008

Ernst, H., Witt, P., & Brachtendorf, G. (2005). Corporate venture capital as a strategy for external innovation: an exploratory empirical study. *r&d Management*, *35*(3), 233-242.

Ernst & Young. (2018). Can corporate venture solve the innovation paradox? Retrieved 02.05, 2019, from EY.com: https://www.ey.com/en_gl/growth/can-corporate-venture-solve-the-innovation-paradox

Fine, J. P., & Gray, R. J. (1999). A proportional hazards model for the subdistribution of a competing risk. *Journal of the American statistical association*, *94*(446), 496-509.

Forbes, S. (2009). Portfolio theory and how parent birds manage investment risk. *Oikos*, *118*(10), 1561-1569.

Gage, D. (2012). The venture capital secret: 3 out of 4 start-ups fail. *Wall Street Journal*, *20*.

Ghosh, S., & Nanda, R. (2010). Venture capital investment in the clean energy sector. *Harvard Business School Entrepreneurial Management Working Paper*, (11-020).

Gompers, P. A. (1996). Grandstanding in the venture capital industry. *Journal of Financial economics*, *42*(1), 133-156.

Gompers, P., & Lerner, J. (2000). The determinants of corporate venture capital success: Organizational structure, incentives, and complementarities. In *Concentrated corporate ownership* (pp. 17-54). University of Chicago Press.

Guo, B., Lou, Y., & Pérez-Castrillo, D. (2015). Investment, duration, and exit strategies for corporate and independent venture capital-backed start-ups. *Journal of Economics & Management Strategy*, *24*(2), 415-455.

Kaplan, E. L., & Meier, P. (1958). Nonparametric estimation from incomplete observations. *Journal of the American statistical association*, *53*(282), 457-481.

Kerr, W. R., & Nanda, R. (2010). Banking deregulations, financing constraints, and firm entry size. *Journal of the European Economic Association*, *8*(2-3), 582-593.

Kleinbaum, D. G., & Klein, M. (2010). *Survival analysis* (Vol. 3). New York: Springer.

Kräussl, R., & Krause, S. (2014). Has Europe been catching up? An industry level analysis of venture capital success over 1985–2009. *European Financial Management*, *20*(1), 179-205

Gompers, P. A., & Lerner, J. (2004). *The venture capital cycle*. MIT press.

Metrick, A., & Yasuda, A. (2010). Venture capital and the finance of innovation. *Venture capital and the Finance of Innovation, 2nd Edition, Andrew Metrick and Ayako Yasuda, eds., John Wiley and Sons, Inc*.

NVCA (2017a). Verdiskapingsanalyse for de aktive eierskapsfondene I Norge 2017: *Såkorn, venture og buyout.* Retrieved 15.05, 2019, from NVCA: http://www.nvca.no/wp-content/uploads/2017/12/NVCA-verdiskapingsunders%C3%B8kelse-2017-Menon-Economics.pdf

NVCA (2017b). Private Equity funds in Norway; *Activity report 2017, Seed-Venture-Buyout.* Retrieved 12. 04, 2019, Retrieved from NVCA: http://www.nvca.no/wp-content/uploads/2018/04/Private-Equity-Funds-in-Norway-2017.pdf

OECD (2017). Entrepreneurship at a glance. Retrieved 14.04 from OECD-iLibrary.org: https://www.oecd-ilibrary.org/employment/entrepreneurship-at-a-glance-2017/venture-capital-investments-in-europe-by-sector_entrepreneur_aag-2017-graph120-en

Rajan, R., Servaes, H., & Zingales, L. (2000). The cost of diversity: The diversification discount and inefficient investment. *The journal of Finance*, *55*(1), 35-80.

Ritter, J. R., & Welch, I. (2002). A review of IPO activity, pricing, and allocations. *The journal of Finance*, *57*(4), 1795-1828.

Rohleder, M., Scholz, H., & Wilkens, M. (2010). Survivorship bias and mutual fund performance: relevance, significance, and methodical differences. *Review of Finance*, *15*(2), 441-474.

Scott, T. W. (1994). Incentives and disincentives for financial disclosure: Voluntary disclosure of defined benefit pension plan information by Canadian firms. *Accounting Review*, 26-43.

Stata (n.d.) Stat glossary. Retrieved 29.04, 2019, from Stata.com: https://www.stata.com/manuals13/stglossary.pdf

Statista. (2019). Total value of venture capital (VC) investments* in Europe in 2017, by sector (in billion euroes). Retrieved 29.04, 2019, from Statista.com: https://www.statista.com/statistics/879228/investments-by-venture-capital-europe/

Sorensen, M. (2007). How smart is smart money? A two-sided matching model of venture capital. *The Journal of Finance*, *62*(6), 2725-2762.

Tian, X., & Wang, T. Y. (2011). Tolerance for failure and corporate innovation. *The Review of Financial Studies*, *27*(1), 211-255.

Wooldridge, J. M. (2012). Introductory econometrics: A modern approach: Cengage Learning. *A Figures*, *18*.

Appendix

A.1 Log-Rank Test

Log-rank test for equality of survivor functions

CVC, IVC	Events observed	Events expected
0, 1	161	150.77
1, 0	15	25.23
Total	176	176.00

chi2(1) = 4.90
Pr>chi2 = 0.0269

A.2 Misspecification Test

	Model 1 Success	Model 2 Success
Predicted	0.955***	0.858***
	(0.131)	(0.113)
Predictedsq	-0.143	-0.158
	(0.113)	(-0.074)
_cons	0.116	0.020
	(0147)	(0.150)

, ** and * denote statistical significance at the 5, 1 and 0.1 percent level, respectively*
Standard errors in parenthesis.
To test for functional form misspecification, we ran a logistic regression where the predicted values and the squares of the predicted values are regressed on the dichotomous dependent variable. Under the null hypothesis, if the model is correctly specified then the square of the predicted values would not be significant. Predictedsq is not significant in both regressions, implying no misspecification.

A.3 Test for Multicollinearity

Variance Inflation Factor

	Model 2			Model 1	
	VIF	1/VIF		VIF	1/VIF
CVC	7.997	.125	ICT	3.799	.263
F3	5.58	.179	Energy	2.559	.391
ICT	4.223	.237	LifeScience	2.528	.396
F5	3.364	.297	Cleantech	2.467	.405
Seed	3.298	.303	Industrial	1.656	.604
Energy	2.913	.343	Consumer	1.42	.704
LifeScience	2.772	.361	Fund activity	1.231	.813
Cleantech	2.64	.379	CVC	1.222	.818
Industrial	1.776	.563	Seed	1.118	.895
F8	1.597	.626	Monthstoexit	1.074	.931
F4	1.587	.63	**Mean VIF**	1.907	
F9	1.492	.67			
Consumer	1.475	.678			
F11	1.472	.679			
F12	1.431	.699			
F13	1.412	.708			
F10	1.393	.718			
F14	1.358	.737			
F17	1.325	.755			
F6	1.317	.759			
F15	1.31	.764			
F7	1.277	.783			
F16	1.247	.802			
F2	1.216	.823			
F18	1.201	.833			
F1	1.19	.84			
M.to.exit	1.179	.848			
Mean VIF	2.187				

The table presents the variance inflation factors (VIFs). The ratios are used as independent variables to estimate the effect of a coefficient due to correlation with other variables. A VIF value above 10 implies multicollinearity between variables. By removing fund activity in model 2, we eliminated concerns regarding multicollinearity.

A.4 Heteroscedasticity test – Model 1

Linear regression Model 1

e2	Coef.(SE)	
Cleantech	-0.363	(0.274)
Consumer	-0.038	(0.393)
Energy	-0.362	(0.272)
ICT	-0.004	(0.239)
Industrial	-0.319	(0.337)
LifeScience	-0.335	(0.267)
Seed	-0.101	(0.133)
Fund activity	-0.007	(0.006)
CVC	-0.174	(0.199)
Monthstoexit	-0.001	(0.002)
Constant	1.437***	(0.293)

Mean dependent var	1.011	SD dependent var	1.169
R-squared	0.031	Number of obs	377.000
F-test	**1.155**	**Prob > F**	**0.320**
Akaike crit. (AIC)	1197.204	Bayesian crit. (BIC)	1240.458

, ** and * denote statistical significance at the 5, 1 and 0.1 percent level, respectively*
Standard errors in parenthesis.
To test whether our models are exposed to heteroscedasticity we conducted a Breusch-Pagan test. If the squared residuals can be attributed to changes in independent variables, there is a problem of heteroscedasticity. The p-value (0.320>0.05) does not reject the nullhypothsis of homoscedasticity. For precautionary reasons, we still include robust standard errors in regression 1. Robust standard errors requires the sample size to be large and our sample size of 377 observations is likely sufficient.

A.4 Heteroscedasticity test – Model 2

Linear regression Model 2

e2	Coef.(SE)	
Cleantech	-0.076*	(0.045)
Consumer	-0.018	(0.064)
Energy	-0.086*	(0.046)
ICT	-0.028	(0.040)
Industrial	-0.084	(0.056)
LifeScience	-0.072	(0.044)
Seed	-0.057	(0.036)
CVC	-0.109	(0.081)
Monthstoexit	0.000	(0.000)
F1	-0.037	(0.062)
F2	-0.094	(0.060)
F3	-0.061	(0.085)
F4	-0.037	(0.043)
F5	0.128	(0.096)
F6	-0.090	(0.063)
F7	-0.052	(0.055)
F8	0.006	(0.049)
F9	-0.017	(0.062)
F10	0.002	(0.062)
F11	-0.020	(0.054)
F12	-0.067	(0.047)
F13	-0.076	(0.050)
F14	0.002	(0.064)
F15	-0.082	(0.058)
F16	0.031	(0.059)
F17	-0.155**	(0.069)
F18	-0.121*	(0.065)
Constant	0.297***	(0.052)

Mean dependent var	0.177	SD dependent var	0.188
R-squared	0.092	Number of obs	377.000
F-test	**1.313**	**Prob > F**	**0.140**
Akaike crit. (AIC)	-171.983	Bayesian crit. (BIC)	-61.881

, ** and * denote statistical significance at the 5, 1 and 0.1 percent level, respectively*
Standard errors in parenthesis.
To test whether our models are exposed to heteroscedasticity we conducted a Breusch-Pagan test. If the squared residuals can be attributed to changes in independent variables, there is a problem of heteroscedasticity. The p-value (0.14>0.05) does not reject the nullhypothsis of homoscedasticity. For precautionary reasons, we include robust standard errors in regression 2. Robust standard errors requires the sample size to be large and our sample size of 377 observations is likely sufficient.