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Interaction amongst independent and corporate venture capital and their influence on exit events

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Abstract

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Interaction Amongst Independent and Corporate Venture Capital and Their Influence on Exit Events

by Daniel Backlund and Filip Örgård

We are studying interaction amongst independent venture capital (IVC) and corporate venture capital (CVC), and how exit events are influenced by IVC and CVC investments, in U.S biotechnology companies between 1977-2018. The research is executed applying both survival analysis and OLS modelling. The hazard ratio towards exit by IPO or M&A transaction is investigated using survival analysis, and how investments by IVC or CVC influence further funding rounds involving the two investor types. The latter part of the paper presents the executed OLS models, invested amount by IVC and CVC is further researched by investigating how earlier investments from IVC and CVC influence current funding, both amount invested in U.S dollars and the investment itself is being researched.

Results from the executed survival analysis indicate that IVCs are more prone to push toward an exit compared to CVC investors. Further, the result indicates that likelihood of further investment rounds involving IVC is negatively influenced by past investments by CVC, whereas CVC involvement is positively affected by earlier IVC investments. Result from the conducted OLS models indicate that both invested amount and the investment itself influence investment decisions by IVC and CVC. Overall, our result indicates that the investor type influence the probability of a potential exit and the likelihood of further investments, and thus it is of importance for companies to appoint best possible investors.

Keywords: *Venture capital, Independent & Corporate Venture Capital, CVC, IVC, Interaction, Biotechnology, Survival Analysis, Panel Data, IPO, M&A, OLS, Exit, Investment Round, Investments*

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1 Introduction

This section presents a brief overview of venture capital investors at first, and differences among investors. Further, review of earlier literature within the field of venture capital is presented and in the latter part is the hypothesises presented and motivated.

1.1 Background

This paper will discuss entrepreneurial financing and the relationship between corporate venture capital (CVC)[1] and independent venture capital (IVC)[2] when seen as investors in newly established entrepreneurial firms. The paper will build upon earlier research within the field of venture capital by e.g Ozmel et al. (2013) and Hellmann et al. (2017), with the aim to further extend the foundation, which entrepreneurial firms may use when making decisions regarding choice of future funding.

Earlier research within the field of entrepreneurial finance in general and venture capital in particular is vast and well explored. However, there are still dearths to be covered concerning research covering multiple sources of funding simultaneously (Bellavitis et al., 2017). Earlier studies mostly cover the different funding sources independently, whereas entrepreneurial firms usually seek funding from multiple sources in the same round of financing. In terms of IVC and CVC are often the dissimilarities between the two types often disregarded from, thus resulting in a biased view towards venture capitalists (VC)[3] and their investment strategies. The interaction between VC and Angel investors have been researched by Hellmann et al. (2017), and we intend to research the interaction between IVC and CVC in a similar way.

Although there are some similarities between CVCs and IVCs in how the organizations are built, with people that have similar backgrounds and with similar mission statements, they differ substantially in overall structure (Gompers & Lerner, 2000). IVCs are structured as such that independent limited partners supply funding and rely on the fund to make profitable investments. Whereas CVCs act as a subsidiary to its corporate parent, which supplies funding and hence the targets and incentives differ between the different types of funds. Moreover, can the horizon for which the funds invest over differ in a significant manner (Chemmanur et al., 2014). IVC funds has a limited life span, which typically is 10 years followed by a potential extension of no more than 2 years. Meanwhile, CVC funds experience so called evergreen funding, implying that they will obtain funding from their corporate

[1] CVC will be used when referring to corporate venture capital throughout the research paper.
[2] IVC will be used when referring to independent venture capital throughout the research paper.
[3] VC will be used when referring to venture capital (including both CVC and IVC) throughout the research paper.

parent for a unforeseeable future. Given the substantial difference in potential length of an investment, it is of interest to establish how these different funds interact with each other in the market. Dai (2007) examines private investments in public equity, and more specifically investments by VC funds and hedge funds, and the research show that investors contributes with different values besides money towards the invested company, in e.g certification of firm value, advising and monitoring the entrepreneurs. Early stage fundraising decisions are critical to the growth and survival of start-up companies. This is especially applicable for biotechnology companies that requires large amount of investments over a long period before they provide any value to the investors. Strategic alliances resolves the information asymmetry problem as well, which is a problem in start-up companies (Ozmel et al., 2013). Earlier studies by e.g Ozmel et al. (2013) show that investments by VC bring more value than money, they certify the companies quality and increase future quality. IVC and CVC investors are various in several aspects, in e.g investment cycles, end-game purpose and strategic alliances. Research by Gompers and Lerner (2001) show that a conflict of interest can occur between various types of VC investors, and if either IVC or CVC invests, it could keep out other investor types.

Looking forward at our thesis, we will in the empirical application compare companies that have received investments by either or both IVC and CVC by measuring the time to exit, as well as investments in each investment round. The data set consists of 2,248 biotechnology companies, with 9,552 unique investment rounds and a total of 27,255 investments by either IVC or CVC. The companies are measured on a monthly basis from founded date until the end of 2018 or if an event occurs in form of M&A transaction[4], IPO, bankruptcy or discontinued. We develop a data set including company characteristics, VC characteristics and market conditions, all which could affect the likelihood of an exit for the company that have received investments.

This thesis is related to a vast amount of literature covering implications of VC investments in start-up companies. Narrowing it down, the thesis is mainly associated towards Ozmel et al. (2013) when researching the influence that IVC and CVC have on different types of exits and investment rounds, applying survival analysis. Further, the thesis is related to Hellmann et al. (2017) in the sections where investment effect from IVC and CVC are investigated. We shed light on independent variables that influence exit outcomes, further motivated from research by e.g Chemmanur et al. (2014), Gompers and Lerner (1997 & 2000), and Stuart et al. (1999).

[4]M&A transaction includes Merger, Acquisition and Leverage buyout (LBO), and will be referred to as M&A transaction throughout the research paper.

To measure the influence of IVC and CVC on exit events, and further investment decisions, we rely on survival analysis and OLS regression model as method. Survival analysis allows us to obtain exit hazard probabilities and robust coefficients with the ability to capture censored events, whereas the OLS model allows us to capture the effect that previous investments have on further investments. Through our estimations, we find positive relationship between IVC and an exit event, and thus in line with hypothesis *H2a*. Moreover, the likelihood of an exit decreases with CVC investments, and thus not supporting hypothesis *H2b*. Further, we find that IVC investments in current rounds are negatively influenced by previous CVC funding, supporting hypothesis *H1a*. Moreover, we find that CVC investments are positively influenced by previous IVC investments, and are thus not in line with hypothesis *H1b*.

The remainder of this paper is structured as follows: The following section motivates the research topic and shed light on previous research within the field of venture capital and interaction between IVC and CVC. Further, the hypothesis are presented and motivated. Section two presents the method applied throughout the thesis, the final models have been derived and motivated. Section three presents the data, containing our final sample and motivation of the included control variables. The fourth section presents the final results, whereas section five presents robustness considerations to the Cox proportional hazard model. Finally, section six concludes this thesis and shares our thoughts related to further research.

1.2 Review of earlier literature

This section presents a brief overview of earlier literature related to entrepreneurial finance, IVC and CVC. This literature review will provide insights to the field of venture capital, and interaction between different investor types. Further, it provides a link between earlier research and this research paper.

1.2.1 Strategic alliances and venture capital

Ozmel et al. (2013) examine the trade-off faced by biotechnology start-ups in the private equity market when choosing between VC and project-level capital from strategic alliance partners. The authors research the effect that these different funding alternatives have on IPO as an exit alternative for start-up companies, and by doing so they further contribute to establish survival analysis and proportional hazard models within the field of finance.

The result from Ozmel et al. (2013) shows that funding from venture capital and alliance formations both has a positive impact on the probability of generating a return at the time of exit.[5] Further, the study finds that venture capitalists and strategic alliances are likely to be counterparts. Such that, in cases where the entrepreneurial firm has sought prior project-level funding from one or more strategic alliance partners, it is less likely that future funding will come from venture capitalists. Suggesting that there is a conflict of interest between the parties, precluding them from investing in the same ventures due to the different purposes behind the choice of funding partner. Capital supplied by alliance partnerships typically tend to be aimed at isolated projects, whereas VC capital are employed horizontally on the entire company.

1.2.2 Angels and venture capitalists

The interaction between angel investors and venture capitalists when investing in early stages of entrepreneurial firms has been examined by Hellmann et al. (2017). The study aims to determine whether the two types of investors act as compliments or substitutes to each other. Further, the study also determines whether there is a difference depending on if the interactions are company- or investor-led.

[5] In addition the study also suggests that the included independent variables affects IPO underpricing and merger valuations. Increased alliance activity prior to an acquisition is associated with higher valuations, and the more investment rounds and increased VC centrality decreases underpricing. Furthermore, biotechnology companies funded by better networked VC companies, with a central position in VC networks, are at substantially greater hazard of going public, and thus increasing the chances of a successful exit for the biotechnology start-ups.

Hellmann et al. (2017) develop a hypothesis they call "parallel streams", building on the assumption that the ecosystem in entrepreneurial finance relies on multiple subsystems (i.e. parallel streams) which all interact with each other relatively infrequently. In such a setting, companies self-select the most suitable investor type for them and are later unlikely to swap investor type. Opposing to the parallel hypothesis, the "stepping stone" approach suggests that it is the characteristics of an entrepreneurial firm that determine which source of funding is the most suitable. Hence, the current investor type will not affect future investor types.

Their study shows considerable support for the “parallel streams” hypothesis, indicating that VCs and angels are in fact substitutes with a pattern which could be explained using the selection effect. Hence, start-up firms which in early stages obtain VC funding, will later be less likely to experience angel funding in additional financing rounds. Furthermore, the study shows support for the hypothesis that different types of companies are better off seeking funding from different investors. In extension to these findings, the study also finds that VCs experience better exit performance than angels do. However, combining the two types of funding will yield a worse result than only choosing one type. The study contributes with important information for local policy makers, who seek to nurture a local or domestic ecosystem for start-ups and entrepreneurial firms.

1.2.3 Independent versus corporate venture capital

Research by LiPuma (2006) and Maula et al. (2005) shows that several factors differs between IVC and CVC investors, whereof main incentive for their investments is one of the factors. The research show that among European CVC funds does 95% have strategic objectives for their investments, whereas 58% of the CVCs have financial objectives in the investment. Further, firms that operates within the same sector as the invested company, strategic fit, are more likely to perform better than companies that received funding from IVCs (LiPuma, 2006).

IVC and CVC bring disparate value to their portfolio companies due to the embedded natures of the funds, compensation differences, as well as investment objectives, and these differences lead to different experiences and quality endowments. CVC add value to their portfolio investments by helping them build commercial credibility and capacity, providing technological support, as well as growth focused activities. Whereas managers of IVC add value in raising additional financing, recruiting key employees, and professionalizing the organization (Maula et al., 2005). The key difference in value adding, is the fact that CVCs often are able to leverage their parent company’s resources in order to generate more value to the portfolio company and a higher valuation at the time of exit (Ivanov and Xie, 2010). However, this effect is mostly noticeable when there exist a *strategic fit* between the corporate parent and the portfolio company.

LiPuma (2006) research mainly focus on internationalization of the firms depending on IVC or CVC funding, and the result displays that CVC provides corporate public credibility for the portfolio firm when entering new foreign markets. However, the result of LiPuma (2006) shows that there is no significant difference between IVC and CVC when looking at internationalization overall.

Maula et al. (2005) research the value-added provided by IVC and CVC when co-investing. Result shows that the value-adding contributions of CVC and IVC are different, but also complementary, in the sense that both IVC and CVC mutually increase the invested company's chances of commercial success.

Research by Gompers et al. (2005) show that venture capital industry is volatile when it comes to fundraising and investment activity, and that the fluctuations are related to changes in the public market valuations and activity. The investment cycles are limited and it is of importance for the investors to invest at correct time, thus to be able to exit when there are high market valuations.

1.2.4 Corporate venture capital, the importance of innovation

Chemmanur et al. (2014) examine how CVC vary from IVC when it comes to value creation and the nurturing of innovation in entrepreneurial firms. Their research aims to bridge the gap in literature concerning how efficient CVCs are compared to IVCs in nurturing innovation in their targeted firms. The authors main hypothesis is that CVCs to a larger extent is more open to experimentation and more tolerant with failures, attributes which should facilitate a higher degree of innovation in their portfolio companies. The logic behind their hypothesis being that CVCs enjoy longer investment horizons, other objectives (not purely financial) with the investment and compensation schemes less dependent on financial performance.

The authors uses a measure based on number of patents a venture has filed for and the number of future citations these patents receives, in order to establish quantity and quality of innovation in the firm and thus its ability to create value. The study is stating that CVC-backed ventures, compared to IVC-backed ventures, are producing a larger amount patents and patents with higher quality. Similar to Chemmanur et al. (2014), Hsu and Ziedonis (2008) also uses patents as a signal for both innovation and firm quality, arguing that patents can ad intrinsic value to the firm due to property rights.

Chemmanur et al. (2014) finds that CVC funds achieve a higher efficiency in nurturing innovation output from their investments. There are mainly two proposed reasons for why CVCs are better at nurturing innovation. The first mechanism being *technological fit*, a measure which tests for how well CVCs corporate parent matches the entrepreneurial firm[6]. A higher degree of strategic fit does, according to the authors, enable CVCs to better nurture innovations in the entrepreneurial firm. The second mechanism behind better efficiency is that CVCs have a higher failure tolerance in relation to IVCs. This suggests that larger volumes of ideas are let through at an early stage and even though this could lead to a higher fail rate, there will also be more successful ideas. With a higher degree of both innovation intensity and quality, Hsu and Ziedonis (2008) find that entrepreneurial firms are perceived in a more positive manner than their peers with lesser amount of qualitative patents, i.e. lower levels of innovation and value creation. The more positive perception is helpful for the venture in multiple stages of its life cycle, in terms of more easily being able to attract initial funding in early financing rounds as well as increasing the IPO probabilities.

1.3 Hypotheses development

The manner in which the two types of venture capitalists nurture and contributes to their portfolio firms is as stated very different. The reason being that they often differ in terms of strategy behind the investment, as well as inheriting differences in organizational structure. Where the main difference between the two being their investment horizons. For example, are CVC funds often funded for an infinite length of time, so called evergreen funding (Chemmanur et al., 2014). The interaction in an investing setting where the two funds are to invest in a certain stage of funding, is thus at the utmost importance. Since it is likely this will affect the entrepreneurial firm subject to the investment. Hellmann et al. (2017) provides insight to the fact that due to the different characteristics angel investors and venture capitalists have, they are likely to act as substitutes to each other in dynamic financing patterns. Similar to this it is thus likely that interactions between CVCs and IVCs also should follow the parallel stream hypothesis.

- H1a: *Ceteris Paribus*, entrepreneurial firms experiencing funding from CVCs are less probable to also receive funding from IVCs after the initial CVC investment.
- H1b: Vice versa, the same should be true for ventures experiencing IVC funding and thus they should be less likely to receive CVC funding after the initial IVC investment.

[6]This measure resembles the one used by both Ivanov and Xie (2010) as well as Gompers and Lerner (200) named *strategic fit*, for continuity measures we will hence refer to technological fit as strategic fit throughout this research paper

Continuing on the previous hypothesis, our second hypothesis is associated towards incentives behind investments by both IVC and CVC. Earlier research by LiPuma (2006) show that only 58% of European CVC funds have financial objectives, whereas 95% out of the European CVCs have strategic objectives. CVC funds are equally with evergreen structure in many cases, which means that they do not have to raise capital, and this in contrast to IVC funds that have limited investment cycles, with other preferences and demands for their investments. Mainly due to demands by their investors (Gompers et al., 2008). Research by Maula et al. (2010) show that value-adding by IVC and CVC are divergent in both origins and consequences. IVC are superior advising their portfolio companies in areas of obtaining funding, recruiting key employees and guidance of developing the organization, as well as deeper experience in supporting entrepreneurs in organizing and preparing for an exit (Maula et al., 2010). Hellmann and Puri (2002) found that IVC played an important role in professionalizing organizations by e.g adoption of stock option plans, faster hiring of marketing presidents and replacing the founder with an outside CEO. Lastly, IVC funds have limited partnerships that pool and manage money from investors, IVC seek high financial returns by funding growth-oriented companies from where the ambition is to exit via IPO or M&A transaction (Dushnitsky et al., 2010). Recent empirical studies does however show that value-adding contributions made by CVC to the commercial success of their portfolio firms may be different from those of traditional IVC (Gompers and Lerner, 2000 & Hellmann, 2002). Result from Dushnitsky et al. (2010) show that exit rates are 9.7% higher for CVC compared to IVC investors, mainly as a result of that CVC usually invest in later stages of the start-ups. Furthermore, we research if likelihood of an exit increases by investments from IVC or CVC in the second hypothesis, and if that could depend on heterogeneity between investor types.

- H2a: The likelihood of an exit increases with investments by IVCs.
- H2b: The likelihood of an exit increases with investments by CVCs.

2 Methodology

This section provides insights in the different methods being applied in our research, survival analysis and ordinary least squares model. Survival analysis will be derived at first, where Kaplan-Meier method is presented first, and Cox proportional hazard model is presented later on. In the latter part of methodology section is OLS model derived, and motivation of the final model is presented.

2.1 Kaplan-Meier method

Survival functions can be estimated with methods using either a non-parametric, semi-parametric or parametric approach. One non-parametric approach is Kaplan-Meier estimator which makes it possible to stratify the survival function into subgroups, between which differences may be tested. This without making any assumptions regarding functional form the survival and hazard function adopts. Kaplan-Meier displays whether there is a significant difference in log-rank between subgroups. Hence, important to evaluate if it is possible to further apply survival analysis on the data set.

Below is Kaplan-Meier estimator

$$\hat{S}(t) = \prod_{j|t_j \leq t} \left(\frac{n_j - d_j}{n_j} \right) \tag{1}$$

where d_j represents number of failures at time t_j and n_j is number of entities at risk at time t_j. The function generates the running probability for a entity to survive the hazard event at time t_j. Hence, Kaplan-Meier estimator takes the number of failures at each time t_j in order to calculate probability of survival.

2.2 The Cox proportional hazard model

Survival analysis measures survival time for an observation to a specific event. The model is mainly applied when censoring problems occur, and when probability is measured over time. The obtained residuals gets scewed and it is not possible to go back and measure the past with other methods. Survival analysis examines covariates' of interaction between two variables, and includes two main functions, survivor function and hazard function, (Kleinbaum & Klein, 2012). T represents time to an specified event and has to be a non-negative random parameter, $T \geq 0$, and the cumulative distribution for time is defined as $P(t \leq T)$. Survival analysis has the ability of capturing censoring in the model, which means that the model captures the effect of an event that does not occur during the specified time period. d represents the random variable, indicating either failure or censorship

$$d = (0,1), \textit{For random variable} = \begin{cases} \textit{1 If failure} \\ \textit{0 Censored} \end{cases}$$

Survivor function in survivor analysis displays probability for the variable of interest to survive longer than the specified time period t, it equals one at t=0 and zero as $t \rightarrow \infty$

$$S(t) = e^{-\int_t^0 h(u)du} \tag{2}$$

Hazard function demonstrate instantaneous potential per unit time for the specified event to occur, given that the variable of interest has survived to time t. Hazard function focus on probability of failing, whereas survival function focus on probability of surviving. If it is possible to calculate one of the parameters, it is possible to determine the missing parameter.

$$h(t) = \lim_{\Delta t \rightarrow 0} \frac{P(t \leq T < t + \Delta t | T \geq t)}{\Delta t} \tag{3}$$

Cox proportional hazard model is a popular model used when analyzing survival data, it is a semi-parametric model, and baseline hazard, $H_0(t)$, is an unspecified function. Further, results from the model are robust, and thus possible to obtain close approximates for hazard ratios of interest.

Below is Cox proportional hazard model

$$h(t,X) = h_0(t) \times e^{\sum_{i=1}^{p} \beta_i X_i} \tag{4}$$

$X_i = (X_1, X_2, ...X_i)$, first part of equation is the baseline hazard function, whereas second part is exponential, $0 \leq h(t, \boldsymbol{X}) < \infty$ always holds. The model gives an expression for hazard at time t with a given set of explanatory variables $\mathbf{X}$ for the variable of interest.

$\mathbf{X}$ is a set of explanatory variables in a vector that predicts individual hazard for the observation. Coefficients are obtained by maximum likelihood.

Hazard ratio in Cox proportional hazard model is defined as the hazard for one observation divided by hazard ratio for another observation. Observations can be distinguished by their values in the set of predictors (the X's).

$$\widehat{HR} = \frac{\widehat{h}(t, \mathbf{X}^*)}{\widehat{h}(t, \mathbf{X})} \tag{5}$$

Where $\mathbf{X}^* = (X_1^*, X_2^*, ..., X_P^*)$ and $\mathbf{X} = (X_1, X_2, ..., X_P)$ denote set of X's for the observations. We have now obtained an expression for hazard ratio, and by substituting the Cox model formula into numerator and denominator of the Hazard ratio equation, final expression after canceling out parts will leave us with the following expression

$$\widehat{HR} = \frac{\widehat{h_0}(t)e^{\sum_{i=1}^{P} \widehat{\beta}_i X_i^*}}{\widehat{h_0}(t)e^{\sum_{i=1}^{P} \widehat{\beta}_i X_i}} = e^{\sum_{i=1}^{P} \widehat{\beta}_i (X_i^* - X_i)} \tag{6}$$

2.2.1 The proportional hazard assumption

An important feature of Cox proportional hazard model is the proportional hazard assumption (Kleinbaum & Klein, 2012). Hazard at time t is product of two quantities. First part of the Cox model (equation 4) is $h_0(t)$, which is the baseline hazard function. Second part from the Cox model is the exponential expression e to the linear sum of $\beta_i X_i$, where sum is over all p explanatory variables.

Baseline hazard is a function of t, but does not involve the explanatory variables (X's), whereas exponential expression involves X's, but does not involve t, and thus the X's in exponential expression are called time-independent X's. Cox proportional hazard model assumes that the hazard ratio is constant over time, this means that hazard ratio for one observation is proportional to hazard for any other individual, whereas the proportionality constant is independent of time.

$$\frac{\widehat{h}(t, \mathbf{X}^*)}{\widehat{h}(t, \mathbf{X})} = \widehat{\theta}, \text{constant over } t \tag{7}$$

If, however, proportional hazard assumption is violated, it is not possible to assign same exponential expression over time.

It is possible, nevertheless, to consider variables (X's) that varies over time t. Such X's are called time-dependent variables. If such variables are assigned to the model, the Cox model could still be applied, but such model does not satisfy proportional hazard assumption, and thus extended Cox model has to be applied.

There are three ways of evaluating if proportional hazard assumption is violated in the Cox model. A graphical procedure, a goodness-of-fit testing procedure, and a procedure that involves the use of time-dependent variables. Further, proportional hazard assumption is presented in Appendix A.4, and is not fulfilled for all variables, and thus the extended model is therefore applied.

2.3 The extended Cox model

As stated earlier, the extended Cox model allows for time-dependent variables. There are two options to consider when the proportional hazard assumption is violated, either using a stratified Cox model, which stratifies on the predictors not satisfying the proportional hazard assumption (Kleinbaum & Klein, 2012). The other option is the extended Cox model, which involves using time-dependent variables, and thus further explained in this section. A time-dependent variable is defined as any variable whose value for a given subject may differ over time, t.

The extended Cox model that includes both time-independent and time-dependent variables

$$h(t, \mathbf{X}(t)) = h_0 \times \exp\left[\sum_{i=1}^{p_1} \beta_i X_i + \sum_{j=1}^{p_2} \delta_j X_j(t)\right] \tag{8}$$

Where $(X_1, X_2, ...X_{p1})$ are time-independent and $(X_1(t), X_2(t), ...X_{p2}(t))$ are time-dependent variables. Further, one important assumption of the extended Cox model is that the effect of a time-dependent variable, $X_j(t)$, on the survival probability t depends on the value of this variable at the same t. The hazard function provides one variable, δ_j, for each time dependent variable in the extended Cox model.

The hazard ratio will change in the extended model as the proportional hazard assumption is violated, and the formula is now a function of time. Further, if δ_j is positive, then the hazard ratio increases with time. Thus, the extended Cox model does not satisfy the proportional hazard assumption if any $\delta_j \neq 0$, or if δ_j represents an overall effect of $X_j(t)$. The last part of the hazard ratio function demonstrates the part of the function that is time dependent.

$$\widehat{HR}(t) = exp\left[\sum_{i=1}^{p_1} \widehat{\beta}_i [X_i^* - X_i] + \sum_{j=1}^{p_2} \widehat{\delta}_j [X_j^*(t) - X_j(t)]\right] \tag{9}$$

2.4 OLS across with cross-sectional elements and time series

When applying ordinary least square (OLS) method with cross-sectional elements and time series, panel-data is often used. A panel of data includes information across both time and space (Brooks, 2012). The following equation shows setting of panel-data.

$$Y_{it} = \alpha + \beta x_{it} + u_{it} \tag{10}$$

Where t=1,...,T, i=1,...,N, Y_{it} is the dependent variable, α is the intercept, β is a $k \times 1$ vector of parameters that is estimated on the explanatory variables, and x_{it} is a $1 \times k$ vector including observations from the explanatory variables.

First, a Hausman test was conducted on the data set to evaluate whether fixed or random effects model is to be preferred. Null hypothesis was rejected (appendix A.2), which tells us that fixed effects model should be applied. The error-term (u_{it}) is then decomposed into two parts. The individual specific effect, (u_i), which affects the variables cross-sectionally but does not change over time. The remaining part of error-term varies over time and entities, (v_{it}).

$$u_{it} = \mu_i + v_{it}$$

Fixed effects model will thereby include both parts of error-term.

$$Y_{it} = \alpha + \beta x_{it} + \mu_i + v_{it} \tag{11}$$

Breusch-Pagan lagrange multiplier has been carried out to test if there is cross-sectional dependence between entities in the model. The test advice to decide whether fixed effect regression model or a simple ordinary least squares regression model can be used. Null hypothesis was rejected (appendix A.2), and concludes that there is a significant random effect in the panel data, thus fixed effect model is able to deal with heterogeneity more desirable than pooled ordinary least squares model.

Modified Wald test is conducted to test for group-wise heteroskedasticity in the fixed effect regression model, it tests whether the variance of error term is dependent on the independent variables in the model. Result of the test (appendix A.2) shows that the model suffers from heteroskedasticity, and heteroskedasticity problem has been solved by applying robust standard errors in the model.

Serial correlation has been tested for by conducting a Woolridge test. Serial correlation causes standard errors of coefficients to be smaller than they actually are and R-squared to be higher. Null hypothesis was rejected (appendix A.2), indicating that model suffers from serial correlation. This problem is solved by using clustered standard errors, dependence within the dependent variable is thereby allowed, but there are still independence between different dependent variables. The final fixed effect regression model will be carried out by applying robust clustered standard errors.

3 Data

This section provides a more detailed description about the final sample of companies as well VC firms invested in the companies. First part of the section displays how the final sample was retrieved, what databases that has been used, as well as summary statistics. The latter part presents motivation of the included independent variables.

3.1 Sample

The initial sample that was retrieved from Thomson Financial's VentureXpert database included 7,475 companies within the healthcare and biotechnology sector. We have decided to limit our research to the biotechnology sector since this sector in its nature is capital intensive with long investment cycles, requiring several stages of funding due to the development process of new technology. Companies in this sector is therefore bound to have received at least one round of financing, thus enabling us to reduce heterogeneity caused by firm quality. After delimiting the data set, our final data set consists of 2,248 private biotechnology companies, with headquarters in the U.S and has received funding from either or both IVC and CVC in at least one financing round between 1977-2018. The sample is not random as all companies have received at least one round of financing from either IVC or/and CVC. Due to these limitations we will apply caution before making any general interpretations about the findings regarding interaction between different types of venture capitalists and their impact on exit performance. Data containing information about the biotechnology company or VC firms has been gathered in Thomson Financial's VentureXpert database. Data that has been gathered for the companies are Company ID, founded date, exit date, what type of exit or status that the company have in the end of 2018, total funding to date, and what state the company is originating from. Data that has been gathered for VC firms are Firm ID, type of investor (CVC, IVC or other investors), invested amount (USD) in rounds, and founded date for the investment firm. The companies are measured on a monthly basis in the data set, and they are measured in that way to capture the effect that investment rounds have. A company could e.g receive funding more than once a year, but is unlikely to receive funding more than once a month. The companies have been measured on a monthly basis because of the employed firm quality variables as well.

Table 3.1: Final biotechnology sample size and applied restrictions.
This table reports our final sample that has been applied throughout the thesis, and how it was delimited after being retrieved from the VentureXpert database.

Sample selection criteria	Sample size
VC firms invested in bio-/medtechnology companies in the U.S (1977-2018)	7,475
Excluding	
Medical/Health/life science companies	(4,624)
No founded date	(123)
Defunct status	(168)
Investment round prior to founded date	(108)
Final sample size	2,248

The companies undergo two events that is of interest, they either go public or are involved in an M&A transaction (Merger, Acquisition or Leverage buyout). Companies that undergo bankruptcy, get discontinued or are still active at the end of the time period have been censored in the survival analysis models, and are not measured further in the conducted OLS models, only active rounds are of interest in the OLS models. Table 4.4 displays the event and exit distribution among companies with earlier CVC or IVC investments. The overall exit ratio is higher in the cases where CVC have invested, whereas M&A transaction is less likely and IPO is more likely.

Table 3.2: Exit and event distribution.
This table reports the event distribution for IVC and CVC investors, as well as detailed event distribution between the two investor types. Both of the investor types could be present in same exit for one companies, it is not limited to companies where only IVC or CVC are present.

Event	CVC	IVC
Exit ratio	49%	44%
IPO	55%	35%
M&A	45%	65%

There is a total of 27,255 investments executed in 9,552 unique investment rounds, whereof 23,529 is investments financed by IVC and 3,726 financed by CVC. In 1,372 of the CVC investment rounds does the parent company of CVC fund interact in same sector as the company that received financing. Table 3.3 presents detailed information of all biotechnology companies, separated by columns representing IVC or CVC involvement. Average number of patents for the companies with CVC investments is significantly higher compared to IVC investments, and thus similar result as earlier research by e.g Chemmanur et al. (2014).

Table 3.3: Time-series data describing the VC involvement in biotechnology firms each year.
Sample consists of 2248 firms where second column presents number of founded firms each year. The following columns is grouped depending on whether there has been a presence of CVC or IVC firms in any funding stage. For each group, statistics is presented for the number of firms that has received funding from the specific type of VC, the number of firms which has gone public, the number of firms which has experienced an exit in form of M&A, the average number of patents held, and the average number of alliance activity by the firms founded each year. NA denotes Not Available for the years where alliance data is missing. Column 3-7 contains statistics over firms which has been subject to CVC investments. Whereas column 8-12 contains firms which has received funding from IVC firms at any stage.

		CVC investment present					IVC investment present				
Year	Firms founded	No. of firms	IPOs	M&As	Avg. no. of patents	Avg. no. of alliances	No. of firms	IPOs	M&As	Avg. no. of patents	Avg. no. of alliances
<1980	39	17	8	6	6.7	0.4	22	10	7	1.6	0.2
1980	15	7	2	5	3.1	1.1	8	4	2	1.6	0.1
1981	34	20	12	7	13.5	0.4	14	3	8	2.6	0.1
1982	16	10	4	5	5.4	0.5	6	3	0	1.2	0.0
1983	26	11	9	2	2.8	0.6	15	7	6	2.3	0.1
1984	14	4	3	1	23.0	1.0	10	3	6	3.5	0.0
1985	18	10	4	5	5.4	0.2	8	2	5	2.8	0.4
1986	21	12	4	7	3.8	1.2	9	5	1	1.4	0.3
1987	38	16	7	8	8.0	0.7	22	9	10	10.4	0.0
1988	29	9	6	3	7.8	0.8	20	7	12	4.7	0.4
1989	25	7	3	4	8.1	0.4	18	7	9	4.0	1.4
1990	22	5	2	3	17.2	0.2	17	6	11	6.9	1.4
1991	21	6	4	1	9.0	0.2	15	5	7	19.0	0.7
1992	48	27	11	11	8.1	0.4	21	4	12	2.4	0.3
1993	39	18	7	7	7.1	0.3	21	3	14	3.4	0.2
1994	40	13	5	7	14.5	1.3	27	5	13	3.6	0.3
1995	43	28	14	7	10.4	0.4	15	2	11	2.2	0.0
1996	51	22	8	11	11.5	0.4	29	4	17	2.8	0.4
1997	66	34	11	13	6.6	0.2	32	2	16	3.2	0.0
1998	60	34	13	4	8.6	0.6	26	4	11	5.7	0.1
1999	58	29	10	10	5.6	0.2	29	4	16	1.8	0.0
2000	89	52	7	20	3.5	0.5	37	4	11	1.5	0.1
2001	76	33	7	9	6.3	0.2	43	6	14	2.2	0.1
2002	69	38	13	9	5.2	0.2	31	3	8	2.3	0.0
2003	83	45	10	18	3.4	0.1	38	4	15	1.3	0.0
2004	70	32	11	6	7.0	0.2	38	6	9	1.7	0.1
2005	90	43	10	9	2.3	0.1	47	5	6	2.3	0.0
2006	113	59	9	12	3.0	0.1	54	6	15	1.9	0.0
2007	94	54	10	10	3.6	0.1	40	4	10	1.4	0.0
2008	103	45	14	5	3.0	0.1	58	5	9	1.1	0.0
2009	81	35	6	5	2.0	0.1	46	7	6	2.1	0.0
2010	70	35	9	3	3.3	0.0	35	4	3	1.2	0.0
2011	103	45	7	3	1.8	0.0	58	5	7	1.0	0.0
2012	69	44	7	2	1.4	0.0	25	3	4	1.5	0.0
2013	97	52	11	6	1.4	0.0	45	8	7	0.9	0.0
2014	76	45	10	2	1.4	0.0	31	3	0	0.6	0.0
2015	112	70	8	2	0.3	0.0	42	2	4	0.4	0.0
2016	68	23	1	0	0.2	0.0	45	0	1	0.0	0.0
2017	46	20	0	0	0.1	NA	26	0	0	0.1	NA
2018	16	5	1	0	0.0	NA	11	0	1	0.0	NA
Total	2248	1114	298	248	5.9	0.3	1134	174	324	2.8	0.2

Patent applications have been manually collected from the United States Patent and Trademark Office (USPTO) database. The company name along with originating states for the biotechnology companies were used to match patent applications. Patent applications registered more than five years prior to founded date have been excluded.
Strategic fit between parent company for CVC fund and the company that received funding is assembled by matching biotechnology SIC codes for the parent company. Included SIC codes can be found in appendix A.3, and Dow Jones FACTIVA database have been used to retrieve all SIC codes.

3.2 Independent variables

Following Ozmel et al. (2013), our independent variables have been categorized into three sections, company characteristics, venture capital characteristics, and market conditions. All variables have been collected on a monthly basis as of the funding date for the company.

3.2.1 Company characteristics

In order to control for different quality metrics within the biotechnology companies, we have included sum of patents last five years, geographical location and strategic alliances last five years. However, we do not have access to company's accounting and ownership information and are therefore not able to control for important drivers, e.g. innovativeness coming from R&D expenditures (Chemmanur et al., 2014).

Following existing literature by e.g Chemmanur et al. (2014), Hsu and Ziedonis (2008), and Ozmel et al. (2013) we employ accumulated patent applications within the past five years as a company quality measure and a measure of innovativeness, quality of the company's scientists or the state of its research portfolio (Ozmel et al., 2013). Moreover, the patent variable operates as a time-varying variable for firm quality as we record the patent applications within the previous five years. Sum of patents have been assembled by registration date for patents in the USPTO database. Sum of patent applications is preferred over R&D expenditures within our sample as the patent applications show the actual innovation output by the company and not only the inputs for attempting to generate innovation. Patent applications as a variable can generate limitations when the sample includes different industries due to various innovation propensity and duration. However, not an issue in this research as the sample is limited towards the biotechnology sector. The same thing arise with limitations within countries and different patent offices, thus not a problem as the sample is limited towards companies with headquarters in the U.S, and therefore only employing patent applications registered at the USPTO.

Two truncation problems occurred when assembling sum of patents. First, several companies received citations in future patent applications, we decided to not include citations. A part of the citations included self citations from future patent applications and a company could receive citations *ex post* to a M&A transaction, IPO or bankruptcy, which generates problems in the data set. Further, the second truncation problem that occurred is that only patent applications have been included, and not whether the patent application actually were granted or not. It is believed that the actual patent applications generates a more true view of innovation, and one of the two could only be assembled due to time limitations, and thus we decided to follow earlier literature by e.g Ozmel et al. (2013).

Following earlier studies by e.g Gompers and Lerner (1997 & 2000), we employ a geographical dummy variable for companies with headquarters located in either California or Massachusetts. The location of the company affects probability of receiving VC investments. Further, CVC investments are more frequent in California, however CVC investments with strong strategic fit are more frequent in other regions (Gompers and Lerner, 2000).

Following earlier research by e.g Stuart et al. (1999), we employ a strategic alliances measure during the past five years. A newly founded biotechnology company entering a strategic alliance relationship, sends a strong firm quality signal to the public and reduces uncertainty about the company and quality (Stuart et al., 1999). The strategic alliances variable operates as a time-varying firm quality variable as well, thus as strategic alliances for the past five years are employed.[7]

3.2.2 Venture capital characteristics

In order to control for the quality of Venture Capitalists included in the sample, we incorporate a number of control variables for VC characteristics. These control variables controls for VC classification, the degree to which each VC type are involved in the portfolio company, the VC investor's influence on other VC investors and lastly whether there is a presence of strategic fit in cases where CVC are investing.

In order to control for VC involvement in each Venture, one would preferably have considered control rights and number of board memberships held by the VC investor. However, the VentureXpert database does not contain statistics for individually held board memberships and other control rights for each individual investor. We have therefore chosen to follow earlier research by Hellmann et al. (2017) and incorporate the amount (in U.S dollars) invested by

[7] The alliance variable only contains data from 1977-2017, we did not have access to the source, and thus relied on the obtained data from earlier research by Fardell and Johansson (2017).

each VC type in an investment round as a proxy for their degree of involvement and control in a venture at that time. This measure is defined as the accumulated amount invested in each specific round by the VC type divided by the total amount invested by all investors in that round.

VC quality is further controlled for by estimating the degree to which VC investors are adopting syndication networks and in extension how large influence they have on other investors. Hochberg et al. (2007) suggests that both capital and an extended range of expertise can be found at VC investors with higher levels of influence. Furthermore, the authors suggest that when VC firms have established a functioning syndication network with other co-investors, they are likely to use these networks in the future, in order to more efficiently find suitable and profitable venture targets. Bonacich (1972, 1987) presents a method which is useful when measuring the closeness between different parties. By using a measure called "eigenvector centrality" we are able to weight the relationship between a investor multiple other parties by the importance of each party the investor is tied to. Congruently with the approach taken by Hochberg et al. (2007) we have adopted the eigenvector centrality method to measure the IVC and CVC investors' influence level. Formally, the eigenvector centrality for VC firm i is defined as:

$$c_{i,t} = \frac{1}{\lambda} \sum_{j=1}^{N_t} A_{i,j,t} c_{j,t} \tag{12}$$

where the presence of co-investment between firm i and firm j is represented by the binary adjacency matrix $A_{i,j,t}$ during the time interval t and *t-5*. $c_{j,t}$ denotes firm j and its degree of centrality at time t. Whilst total sum of active VC investors is denoted by N_t for the observed time interval between t and *t-5*. Lastly, λ denotes the theoretical maximum eigenvector centrality for a syndication network of size n, in form of a normalizing parameter. By weighting a VC's connections, defined as co-investments, to other VC investors, the eigenvector essentially is a measure of the level of influence applied by one VC on its peers. For a more comprehensive interpretation in conjunction with a numerical example, please examine Appendix A.6.

Multiple studies, e.g. Gompers and Lerner's (2000) and Ivanov and Xie (2010), show that strategic fit has an impact on the success of the investment, conforming to these results we employ a dummy variable denoting if the parent company of the CVC operates within a similar industry equivalent to biotechnology, SIC codes for industries are presented in Appendix A.3. The result of Ivanov and Xie (2010) show that it often exists a customer-supplier relationship between the CVC parent and the start-up company, and the parent is often a user of the products from the start-up. Further, 26.8% of the CVCs with strategic fit engage in product development agreements and 17.9% have agreements for joint research. The average equity ownership by strategic CVCs is 21%, whereas only 2% without CVC, and the result displays that strategic CVC-backed IPOs receive significantly higher valuations. Albeit Ivanov and Xie (2010) research is aimed at more than the biotechnology sector, their result shows that it is primarily seen in the biotechnology sector.

One truncation problem occurred when assembling the strategic fit variable, some of the investment transactions retrieved from VentureXpert database are undisclosed, and thus could generate bias as undisclosed transactions could involve strategic fit. It is not possible to correct these values, and one should have in mind that this might generate bias in the strategic fit variable.

We employ a variable including each company i in month t, similar to Gompers and Lerner (2000). This variable represents the average number of months since the investing VC firms were founded, the variable is called "VC firm age, average". The variable is employed to control for duration of the venture organizations, which is a measure of stability in the VC firms (Gompers and Lerner, 2000).

3.2.3 Market conditions

Following earlier literature by e.g Lerner (1994), we employ a variable that captures seasonal effects on the market for IPO and M&A activity. IPO activity in biotechnology firms tend to be positively correlated with high equity valuations, and private equity from Venture Capital tends to be a substitute, primarily received when there are lower multiple valuations on the market (Lerner, 1994). Further, M&A activity is an important indicator of general economic conditions. In order to control for the seasonality effects, we employ Standard & Poor 500 (S&P 500) monthly return index. We employ log-values from the S&P 500 return, mainly to capture deviations from the random walk hypothesis in a more appropriate way, and to obtain a more homogeneous variance from the index (Lütkepohl and Xu, 2009).

Nasdaq Biotechnology Index (NBI) would have been preferred due to greater relevance towards the sample. However, it is not possible to employ NBI as it only reaches back to 1993, and thus S&P 500 captures the seasonality fluctuations on the overall market, which is the main objective for the control variable.

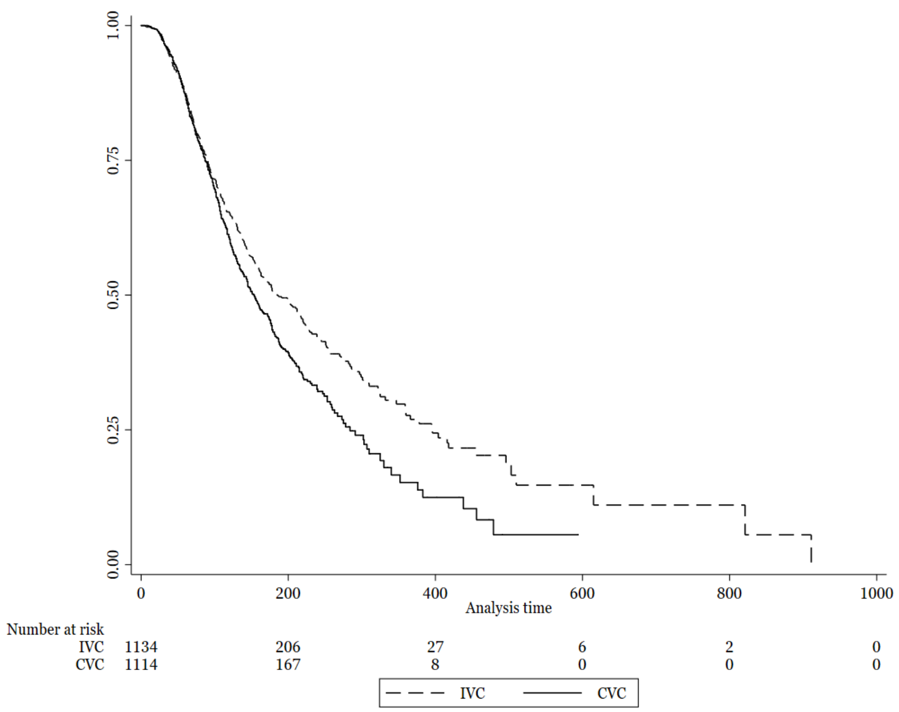
4 Results

This section presents the result from both the incorporated survival analysis model and OLS model. Survival analysis result will be presented at first with the Kaplan-Meier estimator at first, which is a non-parametric approach. Then result from the Cox proportional hazard model is presented. In the latter part of this section is result from the OLS model presented.

4.1 The non-parametric approach

The Kaplan-Meier estimator is used in order to establish whether further survival analysis of the interaction between CVC firms and IVC firms is needed and possible. The firms are grouped into two groups, one containing cases where IVC investors has been present in the investment rounds and one for firms which has received CVC investments at any point. For the two groups, survival functions have been estimated, where the hazard event is defined as an exit through either M&A or IPO. Below in Figure 1, the Kaplan-Meier estimates is displayed as survivor curves. Through the separation between the two curves we are able to establish that firms receiving investments from CVCs, have a higher probability of an exit than firms receiving IVC-funding. At a 1% significance level we can reject the equality of survivor functions via a Log-rank test, hence further survival analysis is necessary. The results from the Log-rank test can be found in Appendix A.1.

Figure 1: Kaplan-Meier survival estimates.
This figure reports the Kaplan-Meier survival estimator, and thus the probability of surviving an event over time. The event is defined as either exit through IPO or M&A, and the analysis time is measured in months from founded date for the observed biotechnology company. The number of biotechnology companies at risk over time, separated by IVC or CVC, are displayed directly beneath the graph.



4.2 Semi-parametric approach

Cox proportional hazard model is performed to evaluate the hazard of different exit options as a function of company characteristics, market conditions and VC characteristics. By employing the Extended Cox Model we are able to account for time-dependent variables. Moreover, by employing the extended Cox model, we are also able to control for censored events. The time-dependent variables will therefore have a significant impact on survival probability for the observed subject. We begin by looking at how the presence of different types of VC investors as well as other investors affect the probabilities of a hazard event occurring. We then further break down the interaction between investors and estimate probabilities for a hazard event to occur given interaction between CVC and IVC investors.

4.2.1 Alternative hazard events

The subhazard estimates of an exit event, in form of either IPO or M&A is presented in table 4.1, as well as for the separate events, conditioned on the presence of at least one type of VC investor. Here the sample is censured by the occurrence of competing events, impeding on the possibility for the hazard event of interest to occur. We find that interaction between CVC and IVC, in terms of investing in the same round, increases the probability of an exit trough either an IPO or M&A by 2.8% compared to if only one of the actors is present in an financing round. Whereas when differentiating between the two exit events, the probability of an exit via IPO increases with 16.9% when CVC and IVC both are involved in a financing round. Regarding an exit via M&A the opposite is found, here the probability of exit is decreased with 5.2%. Further, the amount invested by IVCs is, with high economical significance, a driving force towards an exit of either type. However, the opposite is found when considering the impact amount invested by CVCs in a financing round has on probability of an exit. Instead of promoting an exit through either IPO or M&A, it seems that when CVC firms are a leading investor the likelihood of an exit becomes smaller. In other words, we find that when IVCs are the main investment contributors the probability of a successful exit increases, whereas the opposite seems to be true for when CVCs are the main investment contributors. These findings is slightly contradicting to the findings made by Gompers & Lerner (2000), suggesting that CVC driven ventures are at least as probable as other mainly funded ventures of achieving a successful exit.

Moreover, speaking to the importance of investing in qualitative ventures, are the highly economically significant control variables for company level quality. We find that companies which has filed for a higher number of patents over the last five years, thus proving themselves to be innovative and forward striving, are more likely to encounter a successful exit. With a hazard ratio for sum of patents the last five years ranging between 1.007 and 1.011 for the different exit types at a significance level of 1 percent an exit through IPO as well as for when exits overall are taken into account. Whereas the sum of patents over the last five years is significant at a 5 percent level when looking at exits only through M&A. Altogether we can state that the probability of an exit through either of an IPO or M&A increases by 0.8% for each additional patent a ventures files for. The geographical location of the venture do we find especially important for the probability of a successful exit, increasing the probability of an exit by 28.2% at an 1 percent significance level for companies exiting through IPO or M&A. The impact remains high also when separating between the two events, with a hazard ratio of 1.406 and 1.205 for an IPO exit and M&A exit respectively. These findings strengthen Gompers & Lerner's (1997, 2000) suggestion that venture firms located in either

Massachusetts or California have an advantage when it comes to attracting good venture capital, which in extension could be the explanation to why geographical location has such a significantly high hazard ratio for an event taking place.

Table 4.1: IPO and M&A estimates through interaction between IVC, CVC and Other Investors (OI). This table reports subhazard estimates of exit through IPO or M&A, and the events separately. An observation consists of a given biotechnology company observed on a monthly basis. The dependent variable, exit outcome is defined as one for exit through IPO or M&A and zero for all other events. The other events consists of Bankruptcy, Discontinuation, active throughout the period of observation, and Defunct. "CVC amount" represents the amount in USD invested by CVC per round. "IVC amount" represents the amount in USD invested by IVC per round. "OI amount" Represents the amount in USD invested by other investors per round. "IVC and CVC involved in round" is a dummy variable taking on the value one if IVC and CVC invests in the same round. "Sum of patents, last five years" is the total amount of patent applications within the last five years for an observed biotechnology company. "Geographical location" is a dummy variable taking on the value one if the biotechnology company is located in either California or Massachusetts. "Sum of alliances, last five years" represents the average number of alliances in the past five years. "Rounds" is the number of investment rounds for the biotechnology company since founded. "VC centrality, average" measures the influence from VC, further explained in the data section. "VC firm age, average" measures the average number of months since the founding of the VC firms that have invested in a company, measured on a monthly basis. "CVC investment with strategic fit" is a dummy variable taking on the value one if the parent company of the CVC is originated within biotechnology. "S&P 500 return, 1m" measures the log return for one month of the S&P 500 index.

	IPO or M&A (1)	IPO (2)	M&A (3)
IVC and CVC involved in round	1.028	1.169	0.948
CVC amount	0.994	0.995	0.984
IVC amount	1.014***	1.016***	1.012***
OI amount[1]	1.005	1.009**	0.994
Company characteristics			
Sum of patents, last five years	1.008***	1.011***	1.007**
Geographical location	1.282***	1.406***	1.205**
Sum of alliances, last five years	1.137***	1.270***	0.760**
VC characteristics			
Rounds	1.001***	1.001***	1.001***
VC centrality, average	1.000	0.998	1.000
VC firm age, average	1.001***	1.001***	1.000
CVC investment with strategic fit	1.225*	1.597***	0.967
Market conditions			
S&P 500 return, 1m	0.984***	0.971***	0.996
Number of observations	280,451	280,451	280,451
Number of companies	2,248	2,248	2,248
Number of events (IPO/M&A)	1,044	472	572

***, **, * denote the statistical significance at 1, 5, and 10 percentage levels, respectively.
[1]OI will be used when referring to other investors throughout the research paper.

4.2.2 The presence of CVC and IVC investments

We extend upon research performed by Hellmann et al. (2017) regarding interaction between different investor types, in Table 4.2 below we present the subhazard estimates for different interactions between CVC and IVC investors. We define the hazard event as either an IPO or M&A transaction, controlling for company characteristics, VC characteristics and market conditions. Results (table 4.2, column 8) indicate that companies which experience IVC backing in the previous round as well as in the current round have 98.4% higher probability of a successful exit, at a 1% significance level. Subject to an IVC investment in the current round and at least one CVC investment in the previous round, the likeliness of an exit increases by 17.7% in contrast to if no VC firm at all, invested in the previous round. Consistent with the pattern that IVC investments in the current round increase the likelihood of an exit, is the fact that when the amount invested by IVCs in a round increases so does the probability of an exit according to our obtained result. These findings support the estimates presented in Table 4.1 which also emphasize the importance of IVC involvement in order to increase the probability of an successful exit.

When investigating the relationship between CVC investments in current rounds and IVC investments in previous rounds, we identify that the relationship has a negative impact on the likelihood of an exit by 17.6%. The structural differences between two investors could once again be an explanatory factor. Being that CVC investors believe it to be too big of a mismatch between their different views on how to develop the venture, that it in the long run will not be profitable. Put differently, the presence of strong IVC investors might be an obstruction for CVC investors in being able to leverage their parent companies' resources in value creation purposes, which is common among CVC (Ivanov and Xie, 2010). This relationship supports hypothesis *H1b* in the sense that early IVC funding makes it less likely that CVC investors enters in a later financing round.

Again, the degree to which investors are leading each investment round is having a very small impact on whether an exit is becoming more or less likely. However, similar to the results found in Table 4.1 it is more probable that an event will happen given that IVC investors are involved to a higher degree. At a 1% significance level we find that probability of an exit increases with 1.2% alongside increasing amount invested by IVCs in each round of financing. Whereas for increased amounts invested by CVCs in each round the probability of an exit decreases by 0.2%, thus contradicting our sub hypothesis *H2b*. In other words, when IVCs are the leading investor in a venture, their conviction of making a profitable exit on the original investment supersedes other investors' alternative objectives. Likewise, when CVC investors are the leading authority in a venture, is it their objectives that appear to be the strongest and since they often have more than only financial objectives with an investment the likelihood of an exit decreases.

Similar to the results in table 4.1 we find that the quality of ventures are highly significant in determining the probability of an exit event taking place. With geographical positioning being a key characteristic for ventures in finding investors and having a successful exit event. In the complete model, the probability of exit increases by approximately 20% at a 1% significance level, if the ventures is located in either California or Massachusetts. However, considering the decrease in hazard ratio when adding more controls into the model, one should be aware that this characteristic may be subject to omitted variable bias.

The presented result in table 4.2 show the effect that included control variables have on exit likelihood, and that the influence fluctuates when adding more variables into the model. The purpose of adding further variables in the model is to reduce possible omitted variable biases, and obtain as true result as possible. With the included control variable, we believe that part of biases have been controlled for. However, one should have this in mind and interpret the result with caution.

Table 4.2: Hazard event measured by IVC, CVC, and other investors (OI) scenarios.
This table reports hazard estimates by IPO or M&A. The set up is similar to Table 4.1 with exit event IPO or M&A. This table includes a bigger number of variables, and the ones that was not presented in Table 4.1 have been presented below. "CVC and CVC in previous round" is a dummy variable taking on the value one if CVC invests in the current round, and invested in the previous round. "CVC and IVC in previous round" is a dummy variable taking on the value one if CVC invests in current round and IVC invested in the previous round. "IVC and IVC in previous round" is a dummy variable taking on the value one if IVC invests in current round and IVC invested in the previous round. "IVC and CVC in previous round" is a dummy variable taking on the value one if IVC invests in the current round, and CVC invested in the previous round.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Both IVC and CVC involved in round	1.401***	1.237***	1.165*	1.028	1.028	1.004	0.834*	0.960
CVC and CVC in previous round						1.091		1.037
CVC and IVC in previous round						0.997		0.824
IVC and IVC in previous round							1.624***	1.984***
IVC and CVC in previous round							1.190**	1.177*
CVC amount		0.995	0.994	0.994	0.994	0.994	0.998	0.998
IVC amount		1.017***	1.014***	1.013***	1.014***	1.014***	1.012***	1.012***
OI amount		1.004	1.007*	1.005	1.005	1.005	1.006	1.006
Company characteristics								
Sum of patents, last five years			1.008***	1.009***	1.008***	1.008***	1.007***	1.007***
Geographical location			1.382***	1.266***	1.282***	1.283***	1.218***	1.219***
Sum of alliances, last five years			1.185***	1.149***	1.137***	1.135***	1.131***	1.134***
VC characteristics								
Rounds				1.001***	1.001***	1.001***	1.001***	1.001***
VC centrality, average				1.000	1.000	1.000	1.000	1.000
VC firm age, average				1.000**	1.001***	1.001***	1.001***	1.001***
CVC investment with strategic fit				1.205	1.225*	1.205	1.321**	1.349**
Market conditions								
S&P 500 return, 1m					0.984***	0.984***	0.983***	0.983***
Number of observations	280,451	280,451	280,451	280,451	280,451	280,451	280,451	280,451
Number of companies	2,248	2,248	2,248	2,248	2,248	2,248	2,248	2,248
Number of events (IPO/M&A)	1,044	1,044	1,044	1,044	1,044	1,044	1,044	1,044

***, **, * denote the statistical significance at 1, 5, and 10 percentage levels, respectively.

4.2.3 The likelihood of future investment rounds engaging IVC or CVC

This section reports hazard rates for further investment rounds involving either IVC or CVC. Table 4.3 reports the likelihood of future investment rounds involving either IVC or CVC, and how previous IVC and CVC involvement, as well as other company characteristics affects the probability. The general findings in table 4.3 is that the likelihood of further rounds with IVC investments increases with earlier IVC funding, and in contrast decreases with previous CVC involvement. The likelihood of future investment rounds involving CVC investors decreases with earlier CVC investments and increases with prior IVC investments. The findings associated to IVC is in line with hypothesis *H1a*, suggesting that companies which receive IVC funding conform to the parallel stream theory and tend to stick with IVCs as investors through the majority of their fund raising cycles. Whereas the findings does not support hypothesis *H1b*, instead suggesting that future CVC investments are not alarmed by the presence of previous IVC investors. Hence, when IVCs are present in an early stage, the setting turns more towards stepping stone theory. Earlier research by Chemmanur et al. (2014) show that CVC investors tend to invest in more mature companies, and that IVC are more likely to be involved in early stages. This could explain the obtained result for CVC, indicating that previous IVC involvement influence further CVC investments in a positive manner.

Further, we shed light on the effect that CVC investments with strategic fit have on further CVC investments, which is immense and stands out in the obtained result. Whereas it does not affect further IVC investments in the same manner, both are significant on the 1% level. CVC investors with strategic fit supply companies with more value besides money, providing them with a variety of services and support to their specific needs. In conjunction with their more operational knowledge the information asymmetry, often experienced by external investors, is lowered (Ivanov and Xie, 2010), and hence they are likely to invest in more than one round.

Table 4.3: Likelihood of further investment rounds involving IVC or CVC.
This table reports likelihood of future rounds involving IVC and CVC investments. An observation consists of a given biotechnology company observed on a monthly basis. In contrast to previous tables, the exit variable is defined as next investment round involving IVC or CVC. "Total CVC round" represents total number of rounds involving CVC investors in previous rounds. "Total IVC rounds" represents total number of rounds involving IVC investors in previous rounds.

	CVC (1)	IVC (2)
Total CVC rounds	1.006	0.967***
Total IVC rounds	1.025***	1.036***
Company characteristics		
Sum of patents, last five years	1.000	1.001
Geographical location	1.203***	1.270***
Sum of alliances, last five years	1.089***	1.016
VC characteristics		
VC centrality, average	1.000**	1.000***
VC firm age, average	1.002***	1.002***
CVC investment with strategic fit	3.974***	1.337***
Market conditions		
S&P 500 return, 1m	1.023***	1.005***
Number of observations	280,451	280,451
Number of subjects[1]	4,639	10,638
Number of events (Rounds)	4,623	10,578

***, **, * denote the statistical significance at 1, 5, and 10 percentage levels, respectively.
[1] Subjects represents total number of rounds for all companies, hence all investment rounds are now hazard events.

4.3 Past investments' influence on future CVC and IVC funding

Following Hellmann et al. (2017), we execute an alternative analysis by measuring inflow from IVC and CVC in every investment round. One delimitation has been applied compared to Hellmann et al. (2017), amount invested in current round is being researched, instead of only researching amount from new investors. There are not adequate numbers of CVC observations to measure new inflow, and hence we decided to apply this delimitation. Table 4.4 reports obtained result from the fixed effect model containing investments in current round by IVC and CVC. The amount is measured in U.S dollar to capture the effect that invested amount has on investors decision making. We find that prior IVC investments is significant on all investor types, and that the effect is negative on current IVC investments, whereas it is positive on current CVC investors. Prior IVC is not in line with the obtained result in Hellmann et al. (2017), where prior VC has a positive impact on new VC funding. However, Hellmann et al. (2017) engages both IVC and CVC in the same variable. Prior CVC is only significant on IVC investments, and the interaction between the two is positive, prior CVC have a negative effect on CVC investments, however with insignificant coefficients. The amount invested in previous round is only significant for current round CVC funding, and it affects current funding in a negative direction for both investor types.

Overall, the result indicates that earlier IVC investments have significant impact on investments in the current round, and that CVCs have a significant impact on further investments from IVC. We find that prior amount invested in the companies does impact future funding opportunities, and thus it is of importance for the company to choose proper investors. However, one should have in mind that this reflects upon investments in biotechnology companies in the U.S, and not IVC and CVC investments overall.

Table 4.4: The relationship between prior investments and current investments measured in absolute numbers: Round-to-Round analysis.
This table reports how the invested amount by IVC and CVC in prior and current round interacts with each other, and if investors affects the amount received in current round in separate ways. "Prior IVC", "Prior CVC", and "Prior OI" measures total amount invested in prior rounds by the investor type. "Invested Amount Previous round" measures total amount in USD invested in the previous round, accumulated by all investor types. Standard errors appear in the parentheses below point estimates, and the model is executed with robust standard errors.

	Current IVC (1)	Current CVC (2)
Prior IVC	-0.256**	0.293**
	(0.105)	(0.137)
Prior CVC	0.162*	-0.181
	(0.087)	(0.117)
Prior OI	0.058	0.154*
	(0.056)	(0.087)
Invested Amount Previous Round	-0.069	-0.166**
	(0.044)	(0.066)
Other Controls[1]	YES	YES
Observations	1,629	786
Number of Companies	2,248	2,248
Adj. R-squared	0.457	0.509

***, **, * denote the statistical significance at 1, 5, and 10 percentage levels, respectively.
[1]Control variables contains Centrality, Geographical dummy, sum of alliances last five years & sum of patents last five years.

The contained result in table 4.4 is not in line with hypothesis *H1a* or *H1b*, CVC amount in current round is positively affected by earlier IVC investments, significant at the 5% level. Current IVC amount is positively influenced by previous CVC investments, on a 10% significance level. Taken together the results in table 4.4, findings indicates that time-invariant company characteristics can explain many, but not all parts of investor choices. Insignificant coefficients are consistent with unobservable time-invariant selection effects in a fixed effect OLS model.

Table 4.5 reports the influence that prior investor types have on investments in the current round. It is executed to gather the effect from a specific investor type, and not the amount invested. The coefficients are consistent with previous result from table 4.4 regarding both IVC and CVC. The significance levels for prior CVC have increased, with significant coefficients for current round investments by IVC, and CVC. However, prior CVC investments affect current round IVC investments negatively. The results for prior IVC and CVC are in line with the obtained result in Hellmann et al. (2017) for VC investments.

Table 4.5: The relationship between prior investments and current investments based on dummy variables: Round-to-Round analysis.
This table reports similar structure to the one in table 4.4. However, instead of including absolute numbers, the model is built upon dummy variables. This model is assembled to measure if the involvement from different investor types affects the decision of current round funding for IVC and CVC. "Current IVC dummy" and "Current CVC dummy" is dummy variables taking on value one if the investor type have invested in the current financing round. "Prior IVC", "Prior CVC", and "Prior OI" is dummy variables taking on value one if the investor type has been involved in previous investment rounds. Standard errors appear in the parentheses below point estimates, and the model is executed with robust standard errors.

	Current IVC dummy (1)	Current CVC dummy (2)
Prior IVC dummy	-0.021	0.027*
	(0.017)	(0.017)
Prior CVC dummy	-0.030**	-0.047***
	(0.012)	(0.018)
Prior OI dummy	-0.018**	0.027**
	(0.009)	(0.011)
Other Controls[1]	YES	YES
Observations	7,750	7,750
Number of Companies	2,248	2,248
Adj. R-squared	0.371	0.281

***, **, * denote the statistical significance at 1, 5, and 10 percentage levels, respectively.
[1] Control variables contains Centrality, Geographical dummy, sum of alliances last five years & sum of patents last five years.

The round-to-round analysis result measuring prior investments, show that investments in prior rounds has an effect on future investment decisions. The result in table 4.5 indicates that investments by IVC in the current round is less likely if CVC has invested in any of the previous rounds on a 5% significance level, and therefore we are able to find support for hypothesis *H1a*. On the opposite, no support is found for hypothesis *H1b* since investments by CVC in the current round is positively influenced by previous investments by IVC, with a 10% significance level. Overall, the obtained result in both table 4.4 and table 4.5 indicates that previous investments is influenced by earlier VC investors, as well by other investors.

5 Robustness Considerations

The robustness of the results is tested and discussed throughout this section. First, a motivation of the final Cox proportional hazard model and the decision of time-interaction variables are presented. The latter part of this section includes an alternative approach for the proportional hazard model, where average values have been employed instead.

5.1 Testing the proportional hazard assumption

The Cox proportional hazard model has two main drawbacks. First, application of the method requires an iterative calculation which limits its use for explanatory work. Secondly, the usual interpretation of estimates requires that the proportional hazard assumption holds. If the hazard is not proportional, then there is no clear interpretation of coefficients in the executed model (Kalbfleisch and Prentice, 1981). There are two solutions in case the proportional hazard assumption is not fulfilled. First, one could multiply the variables not fulfilling the assumption with *time*, and thus assemble time-interactive variables. The second solution is to obtain average hazard ratios in the Cox proportional hazard model, and this is further explained in the following section.

Schoenfeld residuals are used in order to test the proportional hazard assumption. It shows whether time dependent covariates is equivalent to a non-zero slope, in a generalized linear regression of the scaled Schoenfeld residuals with functions of time. If the slope is non-zero, then the proportional hazard assumption is violated (Kleinbaum & Klein, 2012). The test displays that "rounds" and "S&P500 return, 1m" violates the proportional hazard assumption (Appendix A.5).

It is also possible to test the proportional hazard assumption by running the Cox proportional hazard model including both untreated variables and variables treated with time-interaction. If significant coefficients are obtained, then the proportional hazard assumption is violated. Appendix A.4 show that the proportional hazard assumption is violated for "rounds" and "S&P500 return, 1m", as noted in the Schoenfeld test as well.

The violation of the proportional hazard assumption is managed by including time-interaction for both "rounds" and "S&P500 return, 1m". This has been executed in the presented result in table 4.1 and table 4.2.

5.2 Alternative interpretation of the hazard ratios

There is an alternative way of interpreting the obtained result in the Cox proportional hazard model, the hazard ratios could be treated by displaying the average values instead (Kalbfleisch and Prentice, 1981). The average values are obtained by running a model including the variables that does not fulfill the Proportional hazard assumption, but without time-interaction. Table 5.1 presents the Cox model with average subhazard estimates including IPO, M&A and both of the exit alternatives as hazard events.

The estimation of the average sample to the total hazard ratio

$$\theta_i(G) = -\int_0^\infty \frac{\lambda_i(t)}{\lambda(t)} dG(t) \tag{13}$$

where i=0,...,k, $\lambda(t) = \lambda_0(t) + ... + \lambda_k(t)$ and G is the survivor function (company is still active). The survivor function (G) is treated equally in the proportional hazard model, even if the proportional hazard assumption does not hold. $\theta_i(G)$ can be interpreted as the ratio of the ith sample hazard to the total hazard of the model, averaged with respect to the weight function, $-dG(t)$ (Kalbfleisch and Prentice, 1981).

The result from the subhazard model (table 5.1) shows that the variables that does not fulfill the proportional hazard assumption, "rounds" and "S&P 500 return, 1m", received high significance levels. The hazard ratio for rounds is higher compared to the obtained result in table 4.1, and lower for S&P 500 return index.

Table 5.1: Cox proportional hazard model excluding time-interacting variables.

This table reports subhazard estimates of an exit, excluding effects of time-interacted variables. The model is executed including time-interaction and without time-interaction for the variables, however only time-interaction coefficients are displayed in the table. The competing events are defined as IPO or M&A event in model (1), only IPO in (2), and merger, acquisition or Leveraged buyout in (3). The subhazard analysis is executed with robust standard errors.

	IPO or M&A (1)	IPO (2)	M&A (3)
Both IVC and CVC involved	1.024	1.163	0.929
CVC amount	0.994	0.995	0.983
IVC amount	1.013***	1.015***	1.011***
OI amount	1.005	1.001**	0.994
Company characteristics			
Sum of patents, last five years	1.009***	1.016***	1.005*
Geographical location	1.198***	1.258**	1.157*
Sum of alliances, last five years	1.140***	1.167***	1.154***
VC characteristics			
Rounds	1.171***	1.1232***	1.132***
VC centrality	1.000	0.996	1.000
VC firm age, average	1.000**	1.001***	1.000
CVC investment with strategic fit	1.141	1.435**	0.926
Market conditions			
S&P 500 return, 1m	0.997***	0.995***	1.000
Number of observations	280,451	280,451	280,451
Number of companies	2,248	2,248	2,248

***, **, * denote the statistical significance at 1, 5, and 10 percentage levels, respectively.

Investment rounds increases the probability of an M&A hazard event in a higher degree compared to IPO and both of the events combined. CVC, IVC, and other investors amount hazard ratios are equivalent to the ones received in table 4.2, but with lower significance levels except for IVC amount.

One should have in mind that the obtained result throughout the thesis could be affected and biased due to scewed data set. The degree of IVC investments compared to investments by CVC are significantly higher. 18.9% of the total amount invested from VC investors in all rounds comes from CVC investors, whereas 80.1% is investments by IVC. One would however need to know the complete dispersion between all IVC and CVC in the United States to conclude whether our sample is scewed towards IVCs or not. Hence, this could generate a scewed obtained result.

Earlier research by Ozmel et al. (2013) includes a "frailty parameter" in the hazard rate estimation to control for unobserved company-level heterogeneity. The frailty parameter reduces biases against the possibility that time-invariant differences against start-up companies drive attractiveness from venture capital or candidates for exit events. One should have in mind that the frailty parameter cannot absorb time-varying firm-level heterogeneity. However, we were not able to assemble the frailty parameter due to core limitations in the software that we had access to, and thus could affect the obtained result throughout the paper.

6 Conclusions

In this thesis we have investigated the interaction between IVC and CVC investors and how their presence in historic funding stages affect future financing of entrepreneurial firms. This has been executed by applying survival analysis in order to compute hazard ratios, explaining how the likelihood of future CVC and IVC funding changes depending on which investor being present in previous funding stages. Our results show support for the hypothesis *H1a*, that previous presence from CVC investors, have a negative impact on future IVC investments whilst having the opposite impact on additional CVC investments. Moreover, the results does not show support for hypothesis *H1b*, instead it seems that previous IVC presence does not repel CVC investors from investing in future investment rounds. This could be a possible result from the fact that CVC tend to invest in more mature companies, whilst IVC tend to invest earlier on (Chemmanur et al., 2014). The interaction between CVC and IVC investors can thus be seen as partially excluding, such that presence from CVC investors prompts IVC investors to be more hesitant to an investment opportunity. Whereas the opposite applies in cases where previous IVC investments is the case, prompting additional investments from both CVC and IVC investors.

Furthermore, this thesis examine the effect each investor type has on the likelihood of a successful exit for U.S biotechnology companies, again making use of survival analysis. Our results suggest that exit events are influenced by both IVC and CVC investors, and thus of importance for biotechnology companies when choosing investors. IVC tend to affect the likelihood of a future exit event in a positive manner, thus supporting hypothesis *H2a*. Moreover, no support is found for hypothesis *H2b*, as CVC investments reduces the likelihood of a future exit.

Considering our additional analysis, applying the OLS method, IVC investments seem to be positively influenced by earlier CVC investments when studying the invested amount, and thus not in line with hypothesis *H1a* or the result that we obtained earlier. Moreover, CVC investments seem to be positively influenced by previous IVC investments, and thus not in line with *H1b*, but in line with previous obtained result. When studying the investment itself, we obtained negative influence on current IVC investments by previous CVC investments, whereas CVC investments are positively affected by IVC. However, instead of following Hellmann et al. (2017) research, we had to investigate the total amount invested in current round, whereas Hellmann et al. (2017) investigates inflow from solely new investors. One should thereby read this part of the result with caution, as it might be misleading and biased.

6.1 Further research

We have studied the biotechnology sector and how IVC and CVC investors interacts within that specific sector in the U.S, we believe that it would be of interest to compare the interaction for IVC and CVC within other sectors as well as for other countries.

In order to reduce possible biases, several company characteristics have been included in this study. To further extend upon this, it would be of interest to employ other company specific control variables that might affect exit hazard ratios or investment decisions by IVC and CVC. Possible variables could in e.g be R&D costs, revenue growth, EBIT margins or capital structure.

Finally, it would be of interest to study invested amount by new investors in the investment rounds, which has been done by Hellmann et al. (2017). However, a larger data set would be desired for doing so.

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A Appendix

A.1 Log-rank test

Table A.1: Log-rank test for equality of survivor functions

CVCDummy	Events observed		Events expected(*)
0	498		552.39
1	546		491.61
Total	1044		1044
	chi2 (1)	=	11.59
	Pr>chi2	=	0.0007

A.2 Conducted tests

Table A.2: Conducted tests for evaluating the data set using panel data.
This table reports the conducted test for determining the final model that is being used for the parts where OLS model is used, and the p-values received from the tests. All of the conducted tests are significant at the 1% significance level.

Test	P-value
Hausman test	0.00
Breusch-pagan test	0.00
Modified Wald test	0.00
Woolridge test	0.00

A.3 SIC-codes

Table A.3: SIC Codes for biotechnology companies
This table reports the SIC codes that have been used when constructing the strategic fit variable. They are used when collecting the parent companies that operates in the same sector as the invested biotechnology company.

SIC codes	Sector
283	Drugs
384	Surgical, Medical, and Dental Instruments and Supplies
807	Medical and Dental Laboratories
873	Research, Development, and Testing Services

A.4 Test with time-interaction variables

Table A.4: Cox proportional hazard model including time-interacting variables and variables without time-interaction.
This table reports hazard ratios for the variables when running the Cox proportional hazard model including both variables with and without time-interaction.

	Hazard ratio
Both IVC and CVC involved	1.001
CVC amount	1.000
IVC amount	1.000
OI amount	1.000
Company characteristics	
Sum of patents, last five years	1.000
Geographical location	1.000
Sum of alliances, last five years	1.000
VC characteristics	
Rounds	0.999***
VC centrality	1.000
VC firm age, average	1.000
CVC investment with strategic fit	0.997
Market conditions	
S&P 500 return, 1m	1.000***
Number of observations	280,451
Number of companies	2,248

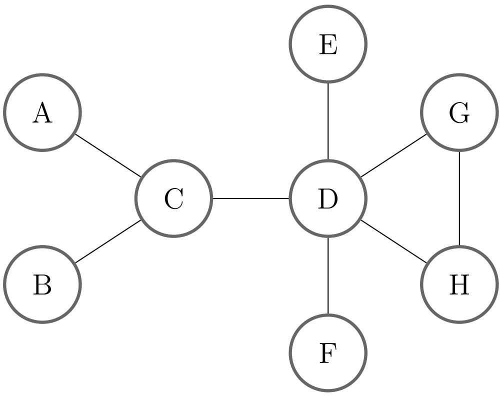
Table A.5: Proportional Hazard Assumption Test Based on Schoenfeld Residuals
This table presents proportional hazard assumption test based on Schoenfeld residuals.

	Rho	Chi2	df	prob>chi2
Both IVC and CVC involved	-0.014	0.200	1	0.652
CVC amount	-0.005	0.020	1	0.885
IVC amount	-0.013	0.200	1	0.267
OI amount	-0.031	1.230	1	0.658
Company characteristics				
Sum of patents, last five years	-0.067	3.120	1	0.078
Geographical location	0.011	0.120	1	0.727
Sum of alliances, last five years	-0.050	0.032	1	0.643
VC characteristics				
Rounds	-0.183	33.550	1	0.000
VC centrality	-0.010	0.000	1	0.986
VC firm age, average	-0.052	2.250	1	0.134
CVC investment with strategic fit	-0.054	3.060	1	0.080
Market conditions				
S&P 500 return, 1m	0.057	3.430	1	0.064
Global test		57.24	11	0

A.5 Eigenvector centrality explanation

Consider a syndication network with eight active parties, in our case venture capitalists, denoted A-H. The relationship between these parties can be represented by the nodes connected by vertices, Figure 2.

Figure 2: An eight actor network of venture capitalists.
This is a visual representation of the venture capital syndication network, with the unidirectional connections displayed as edges between the venture capitalists displayed as vertices labeled A-H.



The adjacency matrix in Table A.6 is another way of representing the syndication network between all active parties. Where the presence of a co-investment between two parties is denoted by one and if the parties does not co-invest this is denoted by zero. In this paper we have only looked at unidirectional relationships and are therefore not recognizing which party is being the leader in the co-investment, hence the symmetry in the adjacency matrix.

Table A.6: Adjacency matrix

	A	B	C	D	E	F	G	H
A	0	0	1	0	0	0	0	0
B	0	0	1	0	0	0	0	0
C	1	1	0	1	0	0	0	0
D	0	0	1	0	1	1	1	1
E	0	0	0	1	0	0	0	0
F	0	0	0	1	0	0	0	0
G	0	0	0	1	0	0	0	1
H	0	0	0	1	0	0	1	0

By using the adjacency matrix (Table A.6) we are able to calculate two different measures of centrality, *degree* centrality and *eigenvector* centrality. Whereas the first measure, degree centrality, simply is the summation of unique parties in a row (or column), i.e. the number of unique interactions a venture capitalist has. This measure is dependent on the number of parties active in the syndication network and it is therefore essential to normalize the measure such that comparability is ensured. The normalization is accomplished by dividing the degree for each actor by the maximum possible connection a party can experience, *n-1*.

An alternative to using degree centrality, is as mentioned to use eigenvector centrality instead. The difference between the two being that eigenvector centrality puts an amplified explanatory power to the degree centrality (Bonacich, 1972 & 1987). In essence, eigenvector centrality is not only taking in to account the number of connections a party has, it also accounts for the centralities of the connected parties. In doing so, the eigenvector centrality is able to capture the level of influence a party has an other parties. As seen in table A.7 the centralities shifts when taking the quality of connections into consideration. Comparing the two measures it is found that the most central actor, D, remains the same. However, actor C drops from being the second most central actor to being the forth most central actor due to lower quality connections compared to its peers. Whilst both actor G and H now are the second most central actors, indicating that they have more influential connections despite their lower number of connections than actor C.

Table A.7: Normalized degree and eigenvector centralities

VC	*Normalized degree*	*Normalized eigenvector*
A	14.3%	19.1%
B	14.3%	19.1%
C	42.9%	49.5%
D	71.4%	89.6%
E	14.3%	34.7%
F	14.3%	34.7%
G	28.6%	56.1%
H	28.6%	56.1%

A.6 Correlation between variables

Table A.8: Correlation matrix.
This table reports correlation between variables that was used in the conducted OLS models. The table tells us that it does not exist any perfect correlation between the variables.

	Time since last round	Age at first round	Geographical location	CVC amount invested in prior rounds	IVC amount invested in prior rounds	OI amount invested in prior rounds	Centrality	Sum of patents, last five years	Sum of alliances	S&P 500 monthly
Time since last round										
Age at first round	-0.021									
Geographical location	-0.000	-0.094								
log CVC amount invested in prior rounds	0.015	0.045	0.135							
log IVC amount invested in prior rounds	-0.005	0.027	0.246	0.564						
log OI amount invested in prior rounds	0.033	0.106	0.144	0.486	0.582					
Centrality	0.056	-0.044	-0.010	0.028	0.044	0.043				
Sum of patents, last five years	0.103	0.089	0.057	0.213	0.286	0.259	0.038			
Sum of alliances	0.048	-0.034	0.016	0.102	0.116	0.076	-0.019	0.156		
S&P 500 monthly	0.021	0.067	0.051	0.350	0.326	0.314	0.076	0.030	-0.092	