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Go-conglomerate, Go-international or Go-local? A comparative overview of Corporate and Foreign Venture capital syndicate investments: funding stage, exit performance and syndicate size

Master Thesis

Abstract

The aim of this study is to analyze at what stage foreign (FVC) and corporate venture capitalists (CVC) are more likely to invest as well as the impact of their involvement on exit performance for various syndicate sizes. By utilizing a pooled cross-sectional dataset between 2000 and 2023 on computer software startups in the United States, I find that both FVCs and CVCs are more likely to invest in later stage startups relative to earlier stages of startup development. Additionally, startups backed by CVC syndicates are more likely to exit relative to IVC syndicates. However, when the exit probability is broken down to more specific exit types, startups backed by FVC syndicates are less likely to exit via an IPO relative to startups backed by a single investor. Moreover, the exit probability decreases as the syndicate size increases for both FVC and CVC syndicate investments.

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1. Introduction

Technology-based startups are becoming increasingly relevant to the US economy. More than 70% of annual VC investments are used for high-technology startups (Gompers and Lerner, 1999). The United States' technology-based startups and venture capitalists provide a crucial competitive advantage in international marketplaces (Freear et al., 2002). Technology-based startups are viewed as having a substantial impact in four specific economic activity areas: innovation, job creation, an increase in export sales and regional development (Knockaert et al., 2010). However, the early resource endowments of these startups are usually concentrated in the knowledge and network of their top management team because many of them are small and have not yet turned a profit (Carpenter et al., 2010). Hence, they turn to Independent Venture capital (IVC) funds to seek additional value such as financial or social capital.

Independent Venture capital (IVC) funds feature an important role in providing growth funding to startups (Hopp and Rieder, 2011), particularly in technology-based industries (Park et al., 2019). In general, the main goal of an IVC fund is to gain high financial returns from investing in relatively high risk and uncertain new startups (Park et al., 2019). Besides providing financial capital to new startups, VCs also provide additional value such as managerial expertise (Hopp and Rieder, 2011). Therefore, VCs are seen as value-added investors to foster innovation in startups. However, it is important to highlight that IVCs are not the only source of funding for startups. One of the alternatives include Corporate Venture capital (CVC) funds. Corporate Venture capital (CVC) refers to the process of established organizations making minority ownership investments in startups, or innovative startups looking for funding to expand (Dushnitsky and Shapira, 2010). What distinguishes CVCs from IVCs is the motivation in investing into startups. Unlike IVCs investing with the expectation of receiving larger financial returns, CVCs make investments with a strategic goal in mind. Examples of such strategic goals opening a window onto valuable, cutting-edge innovative technology to boost company innovation efforts (Dushnitsky and Lenox, 2006).

Moreover, these IVCs and CVCs are not the sole sources of funding for technology-based startups since there has been a recent countertrend in the spatiality of the industry brought on by the presence of foreign venture capital (FVC) funds (Devigne et al., 2018). As domestic VC markets become more saturated, this increases the incentive for VCs to conduct cross-border investments (Guler and Gullen, 2010). Essentially, the share of FVC investments has climbed from 10% in 1991 to 22.7% in 2008 (Chemmanur et al., 2016). Similar to CVCs, FVCs tend to join investment syndicates with multiple VCs to mitigate the risks associated with cross-border investments (Guler and Gullen, 2010). However, there is limited attention being paid towards the investment behavior of FVCs in supporting startups (Mäkelä and Maula, 2005).

Since Schumpeter, startups have been recognized as one of the important drivers for economic growth and competitive advantage in the long run. However, it is still an ongoing policy debate in determining the ideal organizational form to finance new startups' innovation (Chemmanur et al., 2014). Lerner (2012) suggests that while IVCs have contributed a large sum of funding to startups, they have only done so for a few targeted industries. Whereas, despite having a strategic objective to open a new window into cutting-edge innovative technologies, existing literature indicate that CVCs tend to only invest in later-staged startups in which the innovation is already proven and not "cutting-edge" or at the forefront of innovation (Yang et al., 2009; Dushnitsky and Shapira, 2010). One of the solutions Lerner (2012) suggested is to implement a "hybrid" model where FVCs and CVCs join with other IVCs to invest in a particular startup at a particular investment round. This so-called "hybrid" model is widely known as the syndication technique. Syndication is often used by VCs to mitigate investment uncertainty and therefore, improve the exit performance of startups. To measure the success rate or investment portfolio performance, existing literature have used exit performance as a success variable and has measured this through various ways depending on the data availability. It ranges from hard-to-find data such as internal rate of return and different exit types to simply computing a binary variable of whether the startup has exited or not (Stuart et al., 1999; Dai et al., 2012; Cumming et al., 2016). Despite a few existing literatures utilizing exit performance as a measure, exit performance is still rarely examined as a success metric (Streletzki and Schulte, 2013). In this study, I use exit probability as a metric for startups' exit performance; that is, how likely a startup would exit the market.

All in all, this study examines the investment practices that IVCs, CVCs and FVCs use to mitigate investment uncertainty: staging (i.e., investing in particular stages of a startup's development) and syndication (i.e., coinvesting with at least 2 or more VCs). Additionally, this study will look at how the syndication technique affects the exit performance of startups. Hence, this brings us to the main research question of this study-

Relative to IVCs, do FVCs and CVCs differ in their investment preferences across different stages of startup development and how do each type of VC syndicate impact the exit probability of startups?

This study provides several contributions to the existing venture capital literature. Firstly, this study analyzes the impact of FVC syndicate participation within a developed economy. Current existing literature analyzing FVCs have predominantly used samples from emerging economies or any other country outside of the United States due to FVCs were mostly generated from developed economies to invest into emerging economies (Pruthi et al., 2003; Mäkelä and Maula, 2005; Guler and Gullen, 2010; Dai et al., 2012). However, there is an increasing trend in which VCs from emerging economies are investing into developed economies such as the US. Hence, this study extends this literature by analyzing how FVC and CVC syndicates may bring additional value or risk towards startups within a developed economy, specifically the US. Secondly, this study is, to my knowledge, the first study that provides a syndicate-level analysis of FVC and CVC syndicates. FVCs and CVCs may not only pose additional risk to other investors in the syndicate. Instead, FVCs may provide additional benefits particularly towards the exit probability (Cumming et al., 2016; Park et al., 2019) and these benefits are different relative to CVCs. Therefore, the exit probability of FVC syndicates may differ largely relative to CVC syndicates. By extending the work of Cumming et al. (2016) and Park et al. (2019), this study addresses the participation of FVCs and CVCs in syndicates with a deep dive on different syndicate sizes. Lastly, this study also contributes to the CVC literature (Gompers and Lerner, 2000; Dushnitsky and Lenox, 2006; Dushnitsky and Shaver, 2009; Dushnitsky and Shapira, 2010; Fulghieri and Sevilir, 2009). Current CVC literature focuses on the strategic benefits CVCs provide (Gompers and Lerner, 2000; Dusnitsky and Lenox, 2006) alongside the risks of being invested by a CVC (Dushnitsky and Shaver, 2009). Hence, this paper extends that view by looking at whether those benefits and risks associated with CVC are reflected within the exit probability and syndicate size context.

2. Literature review

In essence, significant cross-border investments have characterized the globalization of venture capital in entering new markets (Pruthi et al., 2003). While recent trends show significant increases of cross-border investments in emerging countries, the FVC concept started several decades ago in a developed country, the United States. Among the earliest instances is the 1982 establishment of the first Japanese venture capital fund in the United States by the Japanese company JAFCO (Hurry et al., 2022). Their main goal was to join the cash-rich businesses that had started to invest in high-tech projects in the US before JAFCO was founded. Since then, FVCs have become more prominent within the US venture capital industry and provided several benefits to local startups. These benefits include FVC funds offering more extensive global networks and easier access to finance and overcome negative local exit conditions, among other advantages (Bertoni and Groh, 2014). Despite the benefits of FVC funds, they are frequently limited by the information asymmetry caused by the spatial distance between the FVC fund and the startups.

2.1 FVC investment practices

By concentrating on projects that are in particularly later stages, the exposure to risk such as information asymmetry can be controlled (Dushnitsky and Shapira, 2010). Current literature shows that spatial distance and institution differences matter to collect information-based financial activities especially in VC investments. For example, US startups when located in proximity of their VCs are more likely to successfully exit via IPOs or M&As after adjusting for startup quality and reputation (Cumming and Dai, 2010). Similarly, Moore et al. (2015) find that increases in normative and cultural-cognitive distance reduces foreign VC investments. The institutional differences between the home and foreign country could hamper different aspects of the startups' performance such as realizing intended strategies (Dobrev and Carroll, 2003) and adopting new organizational policies and practices (Kostova and Roth, 2002). Building on these studies, it seems likely that the decisions of FVCs to invest in the United States would incur so many risks towards the FVCs, as it is challenging for FVCs to proceed relationships with more transparent firms and the geographic distance makes close monitoring difficult (Dai et al., 2012). Therefore, foreign VCs would refrain from funding informationally opaque companies to lower costs resulted from asymmetric information. IVCs, however, have an informational advantage relative to foreign VCs particularly regarding the deal flow, the local network they possess and the expertise within the local legal requirements (Pruthi et al., 2003).

2.2 CVC Investment Practices

In the US, CVCs were established relatively earlier than FVCs. Specifically, US corporations started CVC funds as early as the mid-1960s (Gompers and Lerner, 2000; Chemmanur et al., 2014). Moreover, unlike IVCs that tend to invest in new startups with the sole motivation of increasing financial returns (Gompers and Lerner, 2000), CVCs tend to invest with a strategic motivation (Chesbrough, 2002). A CVC investor's main motivation is usually to gain access to the startup's cutting-edge information and technology (Park et al., 2019). Hence, CVC is mostly identified as a window to new technologies (Maula et al., 2013) where they are seeking for potential innovation disruptors by gaining access to the information and technology. Additionally, relative to IVCs, CVCs are more effective at boosting the new startups' public perception, luring clients, partners, and suppliers, and promoting technical advancement (Maula and Murray, 2001).

Despite the benefits that CVCs provide towards new startups, existing literature portrays mixed views on CVCs' investment practices. Chemmanur et al. (2014) find that CVC-backed startups are typically younger, have higher uncertainty, and are less profitable than IVC-backed startups. On the other hand, Fulghieri and Sevilir (2009) discover that IVCs appear to be more desirable for early-stage startups while CVCs appear to be more desirable for later-stage startups through the impact of competition on ideal organizations and finance structures of innovation-intensive sectors. Similarly, through the principal-agent framework, Dushnitsky and Shapira (2010) find that, on average, corporate investment practices focus on startups with diminishing investment uncertainty. Hence, CVCs are likely to target late-stage startups. Yang et al. (2009) also find that CVC performs better in terms of experience accumulation if the CVC funds invest in later stages of startup development rather than early stage.

Besides the current view on CVCs' investment practices, it is important to also highlight the industry sector relevance of the sample used in existing literature. The only authors that solely focus within the technology sector are Dushnitsky and Shapira (2010) and they implied that CVCs invest in later stages. Knowing that this study analyzes the technology sector, I expect that:

H1: An investment round led by a foreign or a corporate venture capital is more likely to occur at the later stage of startup development

2.3 Syndication and Exit Probability

Syndication is the involvement of numerous investors in an investment round. VCs use syndication as an instrument to mitigate risks such as financial risk exposure (Brander et al., 2002; Dushnitsky and Shapira, 2010) and information asymmetry (Dai et al., 2012). According to the syndication theory, when investors are unable to invest in multiple startups, they may turn to syndication as a form of risk-sharing mechanism when faced with uncertain payoffs (Dushnitsky and Shapira, 2010). Other than mitigating risks, syndication also serves the benefit of providing multiple networks for the startups and therefore, increasing access to information and improving monitoring capacities (Park et al., 2019).

Moreover, FVCs have been an integral part in syndication practices. Existing literature has outlined the positive impact of having an FVC as part of the syndicate (Bertoni et al., 2014; Dai et al., 2012; Cumming et al., 2016). Besides the extensive global networks, easier access to finance, and overcoming negative local conditions (Bertoni et al., 2014), FVCs can increase the probability of a startup to exit through IPO or acquisitions (Cumming et al., 2016). Moreover, with the aid of IVCs, the cultural and geographic distance between the startup and the FVCs reduces conflict leading to better monitoring and selection (Dai et al., 2012). Hence, these advantages would increase the value of the startup and, most of all, the probability for startups to exit.

Likewise, CVC has also been a prominent actor in syndication practices (Gompers and Lerner, 1998; Dushnitsky and Lenox, 2006; Chemmanur et al., 2012). Gompers and Lerner (1998) find that syndicated startups that are backed by CVC syndicates with strategic intentions are more likely to go public relative to those that are financed by other financially driven organizations.

Additionally, Dushnitsky and Lenox (2006) depict a positive relationship between CVC and firm value creation. In particular, the authors emphasize that the effect is greatest within the technology sector. More importantly, syndication allows CVC-backed startups to be endorsed by multiple organizations leading to a greater exit probability (Stuart et al., 1999). Chemmanur et al. (2012) report that CVC-backed startups have greater post-IPO long-run stock returns. Hence, with respect to the current literature views, I expect that:

H2: A syndicate led by a foreign or corporate venture capital positively affects the exit probability of startups.

2.4 Syndicate size and Exit Probability

Alongside the other important characteristics of VC syndication, the size of the syndicate has a fundamental impact on how well the startup performs (Hambrick & D'Aveni 1992; Zhang, Gupta, and Hallen, 2017). Thus, this indirectly affects the exit probability of a startup (Devigne et al., 2013). The consensus of having a large syndicate size is varied. On one hand, having a large syndicate brings resource benefits such as broadened networks, increasing access to knowledge and monitoring capabilities (Kim and Park, 2021). More importantly, a larger syndicate would lead to lesser ownership holdings by individual VCs, giving the startup CEO more relative influence in comparison to any other VC (Garg, 2013). A larger syndicate also reduces the risk of not being able to secure needed investments in the second or later rounds (Zhang, Gupta, and Hallen, 2017).

On the other hand, having too big of a syndicate may lead to coordination costs. One of them includes the communication complexity problem whereby the lead investor requires more focus to manage the syndicate at the expense of monitoring the startup, hence, this may impact the probability of the startup to exit (Jääskeläinen et al., 2006). The necessity for communication on decision-making increases with the number of participants yet setting up an in-person meeting with a larger number of partners becomes challenging. Even if the partners can convene in the boardroom, it will be challenging to come to a consensus given that there are so many VC companies contributing diverse viewpoints and ideas (Kim and Park, 2021). Moreover, given the vast array of VCs often present in syndicates and the probability of competing preferences and purposes among them, existing literature propose that coordination and free-riding issues are likely to affect large VC syndicates as well (Hellmann et al., 2008; Chemmanur et al., 2011). While greater syndicates "provide valuable learning opportunities for the group members in the long term," according to Du (2016) who examines the dynamics of heterogeneous venture capital syndicates, it also makes internal communication and coordination less efficient.

Overall, we can draw that the advantages and disadvantages of having a larger syndicate are mainly driven by resource benefits and coordination costs, respectively. However, looking at the point of view of FVCs, it is important to stress on the cultural and geographic distance between the startup and the FVC. Although syndicating with IVCs could aid the monitoring and selection process, having a larger syndicate with more IVCs could increase the chances of culture conflict and having an inefficient decision-making process due to the potential communication complexity problem. Likewise with CVCs, recall that the main objective of CVCs is to gain access to the startup's cutting-edge information and technology (Park et al., 2019). The strategic objectives that CVCs have may conflict the financial objectives that IVCs have. Therefore, the greater the number and variety of IVCs within a CVC syndicate would result in greater probability of strategic conflicts. Overall, the impact of a high number of syndicate partners will likely result in a decline in the exit probability (Jääskeläinen, Maula, and Seppä, 2006; Kim and Park, 2021). Therefore, I hypothesize that:

H3: The syndicate size of an investment round negatively affects the relationship between the foreign or corporate venture capital syndicate and the exit probability of a startup.

3 Data and Methodology

3.1 Data and Sample Selection

The sample within this study is a pooled cross-sectional dataset that consists of all US-based computer software startups resulting in 20,451 observation rounds of venture capital investments. Specifically, I include startups that are operating in the computer software sector classified as Venture Economics Industry Code (VEIC) 2700. Within this industry, there are VEIC sub-groups operating in different areas of the computer software industry which will be controlled in the analysis (see Appendix, table A1). These investments are invested by IVCs, CVCs and FVCs between 2000 and 2023 as documented by Refinitiv Eikon database. Formerly known as Thomson Reuters, Refinitiv Eikon is a specialized database that has 70 years' worth of firm-level information for all asset classes. To identify whether a startup has been invested by a FVC or a CVC, I extracted startups that have a FVC or a CVC participating for any round of investment. Moreover, to avoid any possible outliers, I only included startups that were founded after 1990. The reason for dropping startups that were founded specifically before 1990 is because the average lifetime of a startup is 10 years (Davila et al., 2003) and since the earliest investment year within the dataset starts at the year 2000, including startups founded before 1990 would mean that the startup has been operating for more than 10 years before it received its first investment at the year 2000. In addition, current literature also pointed out that there are limited data collection possibilities in the early nineties which may cause inaccuracies in the analysis (Bertoni and Groh, 2014). Davila et al. (2003) also pointed out that startups operating before the 1990s generally take 10 years on average before receiving their first investment. I also dropped startups that are bankrupt or startups that are inactive.

Other than that, I dropped observations with duplicates in terms of investment year and syndicate size. Several observations report investment year and syndicate size duplicates (see appendix, table A2). Including these observations would violate the independence assumption between startups. Moreover, for simplicity of the analysis, I dropped observations that are invested by foreign CVCs or startups with both CVC and FVC as equal participating investors. Further, I dropped observations with round numbers and syndicate sizes greater than the 99th

percentile specifically to remove outliers reporting mistakes that may potentially affect the results (see Appendix, table A6 and A7). The reason for dropping these observations is because there were a couple of round number and syndicate size datapoints that were far from the average, which can impact the accuracy of the results (Liu, 2020). Lastly, I dropped observations with incomplete or missing data. Hence, this leads to a final sample of 12,098 observations with 9,024 different startups.

3.2 Variable Operationalization

In this section, I present the variables that will be used in this study. Before deep diving into the variables, it should be noted that several variables might be highly correlated with each other. However, I find that most of the variables are not highly correlated with each other. Specifically, most of the coefficients are less than 0.4 (see Appendix, table A4). I did not find any high correlation among the independent variables since the independent variables of interest (that is, investment, syndicate, and syndicate size variables) do not depict correlations with most of the other independent variables greater than 0.4. Still, there are several notable variables that are highly correlated with each other. This includes invyear and age (0.872) and round number and stage (0.542). However, it is important to note that these correlations are either between a control and dependent variable or between control and another control variable. Hence, if it is not correlated with the independent variable, the correlation should not impede the results validity. On top of that, the VIF table indicates all the variables are below 6 (see Appendix, table A5).

3.2.1 Dependent Variables

$Stage_{jt}$. Investors use a variety of strategies to control for the amount of risk they encounter (Gompers and Lerner, 2000). I consider the stage of development, $Stage_{jt}$, of the startup j at the year of investment t as one of the main dependent variables. As in Dushnitsky and Shapira (2010), startups undergo different stages of financing. It is important to highlight that as startups mature, the technical viability, commercial viability, and management capacity problems of the startup are resolved (Gompers and Lerner, 2000; Dushnitsky and Shapira, 2010). This reflects the importance of startups being an ordinal variable as previously mentioned by Dushnitsky and Shapira (2010). Figure 1 provides a clear characteristic description of each stage of development showing that each stage is different and certain characteristics must be fulfilled to proceed to the subsequent development stage. Refinitiv Eikon provides the stage of development of each startup at the time of the investment round. This variable is a categorical variable mainly used to investigate the probability of FVCs or CVCs investing in startups at different stages of development. Like Dushnitsky and Shapira (2010), this variable is defined into four key stages based on the Refinitiv Eikon definitions: seed, early, expansion, and later stage, and I set the values of the investment stages to 1, 2, 3, and 4, respectively. Table 1 depicts the stage of development distribution, and it is evident that startups within the early and expansion stage are the most frequently appearing startups within the dataset.

Figure 1 Characteristics of each stage of startup development before IPO

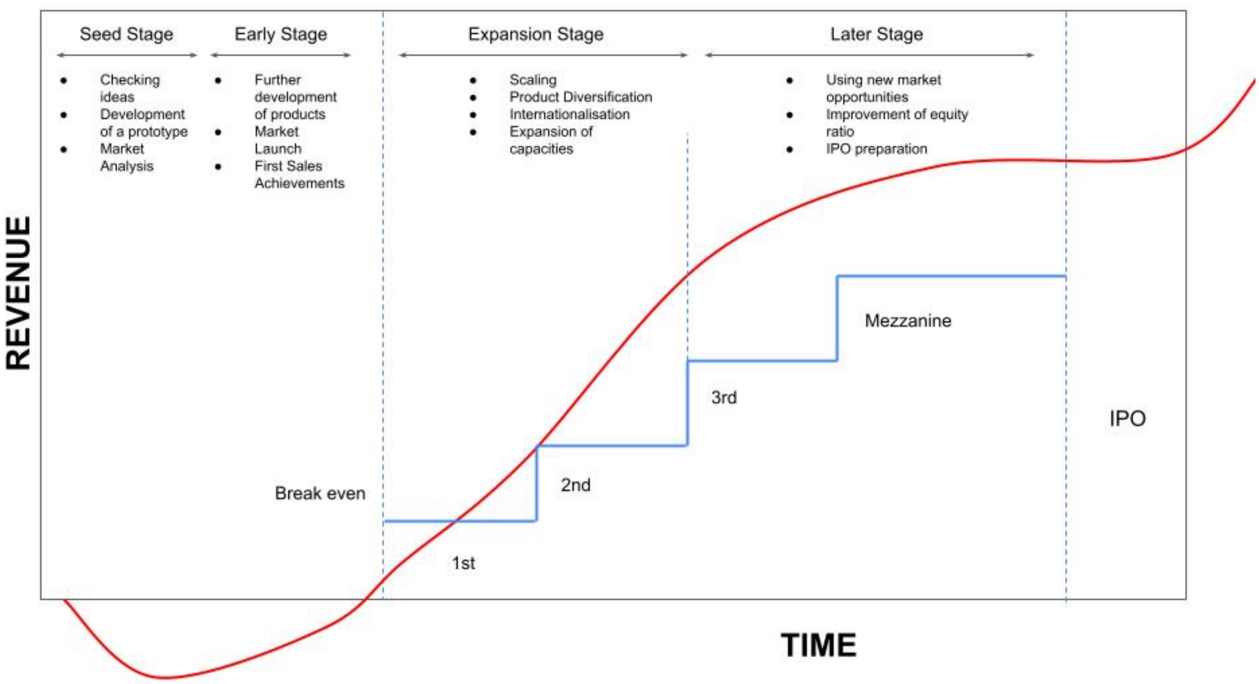


Table 1 Stage of Development distribution for computer software startups

Stage	Frequency	Percentage
Seed	883	7.30
Early	5,732	47.38
Expansion	3,773	31.19
Later	1,710	14.13
Total	12,098	100.00

$Exit_j$. In an ideal scenario, a fund's internal rate of return across its 10-year lifespan would be used to directly gauge performance of the startup. However, VC funds often only share their results with their investors, and Refinitiv Eikon only makes fund returns publicly available in aggregate form, thus returns for individual funds are not always readily available. As an alternative, we gauge fund performance indirectly by using the exit status. Ljungqvist et al. (2005) claim that the typical venture capital fund drops 75.3% of its investments. This suggests that VC firms only make financial gains from a tiny portion of the companies in their portfolio that are sold through different types of exits such as an acquisition, IPO, or an M&A deal (Hochberg et al., 2007). Hence, to investigate the second and third hypotheses, I will use a dummy variable namely, $Exit_j$. $Exit_j$ is defined as the type of exit the startup has experienced. This variable is time-invariant as Refinitv Eikon does not disclose at which specific year the startup has undergone the exit. Based on the Refinitiv Eikon definition, the different types of exits observed within this dataset includes Acquisition, Leveraged Buy-Out (LBO), Mergers, Pending Acquisition and IPO. If the startup has not undergone any exit, the status of the startup is labelled as “Active”. Hence, based on this definition, $Exit_j$ is equal to 1 if a startup has exited the market either through an Acquisition, Leveraged Buy-Out (LBO), Mergers, Pending Acquisition, or an IPO. $Exit_j$ is equal to 0 if the startup is still labeled as “Active”.

3.2.2 Independent Variables

3.2.2.1 Investment Variable

$FVC\_invested_{jt}$ and $CVC\_invested_{jt}$. To investigate the first hypothesis, I include separate dummy variables accounting for the presence of either an FVC or CVC as their investor of startup j at the year of investment t. Chemmanur et al. (2016) defines the FVC variable classification as follows: if the office of the VC fund is not situated in the same nation as the startup, it is an FVC. More importantly, Chemmanur et al. (2016) also uses the Venturexpert database (now integrated into Refinitiv Eikon) which is the same database used for this study. Following Chemmanur's definition, $FVC\_invested_{jt}$ is equal to 1 if the headquarters of at least one of the VC investors is in a nation outside of the US and 0 otherwise. As for CVC backed startups, the Refinitiv Eikon database has a feature that simply identifies whether the startup is invested by a CVC or not. Hence, $CVC\_invested_{jt}$ is equal to 1 if there is at least one CVC investor present in the investments and 0 if it is not invested by a CVC. Moreover, it is important to highlight that $IVC\_invested_{jt}$ will be the reference variable throughout the analysis for hypothesis 1. In this study, all IVCs have headquarters only in the US.

3.2.2.2 Syndicate Variable

IVC_syn_{jt}, FVC_syn_{jt}, and CVC_syn_{jt}. Moreover, I also use separate dummy variables that identify whether the IVC, FVC or CVC invests within a syndicate for a startup j at investment year t. To create this variable, I filtered the startups based on two criteria: whether the startups have 2 or more investors per round and whether it has an IVC, FVC or a CVC participating in the investment. It is important to highlight that some startups within this dataset are only invested by a single investor. Hence, for this variable specification, IVC_syn_{jt} is equal to 1 if there are two or more investors within an investment round invested only by IVCs and 0 otherwise. This applies also to FVC_syn_{jt}, and CVC_syn_{jt} where the dummies will be equal to 1 if there are two or more investors within an investment round invested with at least one FVC and a CVC, respectively, and 0 otherwise.

3.2.2.3 Syndicate Size Variable

$Syndicatesize_{jt}$. Existing literature defines syndicate size as the number of investors that took part in a particular investment round (Terjesen et al., 2013; Zhou et al., 2016). Moreover, existing studies have also identified several measures of syndication including VC syndicate size or using a simple indicator denoting whether or not many VCs invested in a particular startup (Lerner, 1994; Nahata, 2008). To investigate the syndicate size effect, I will be using the continuous number of investors as a measure for syndicate size. Specifically, this variable is a continuous variable that considers the number of investors investing for a particular startup j at investment year t.

3.2.3 Control Variables

The set of main control variables aims to address confounding effects within the observations and to control for unobserved heterogeneity within the analysis. Below are the variables that are controlled for-

$rnumber_{jt}$. I include the investment round number defined as the specific phase or stage in the process of raising capital for a startup j at investment year t. This variable is a count variable which records at which particular round the startup is invested at investment year t. I argue that the round number positively affects the stage of development and the probability to exit. The reason behind this argument is because the first round of financing typically has greatest risk. The initial round of VC investors' certification leaves subsequent rounds considerably less risky (Lerner, 1994) where typically startups invested in subsequent rounds are already at their expansion or later stage of development. In terms of syndication, aligned with the argument that FVC and CVC syndicates tend to avoid investing in informationally opaque startups, it is justified that startups in later rounds are more likely to be invested by syndicates since they are relatively more mature and less risky relative to early-stage startups. Hence, we control the confounding effects resulted by the round number of the startup.

age_{jt}. Moreover, I include a continuous variable that identifies the age of the startup as one of the control variables. Essentially, I calculate the age of the startup as the difference between the founded year of the startup and the latest year within the dataset that is 2023. This is to control the confounding effect that age may have towards syndication and the exit probability of the startup. Zhang (2007) find that the later the founding year, the easier for the startup to gain startup funding reflecting the fact that venture capital is becoming increasingly available in later years. With that being said, I argue that younger startups (startups founded in later years) are more likely to have greater exit probability as they have greater total funding. Hence, I add the age of startups as a control variable to control for the confounding effects.

$Logtotalfunding_{jt}$. Additionally, I include the total funding amount of each startup captured at each funding round. Total funding amount is considered as one of the determinants of VC fund performance (Kaplan and Schoar, 2005; Hochberg et al., 2007), since the total funding amount positively influences the performance of a startup (Hochberg et al., 2007). The higher the total funding amount, the more resources a startup may have to improve their operational efficiency. Total funding amount also reflects the number of investors in a syndicate investing for a particular startup. Specifically, the greater amount of funding would indicate a greater probability of VCs investing into the startup. Moreover, it is important to highlight that the total funding variable is heavily skewed and has a wide range of magnitudes. Figure A1 depicts a histogram of the total funding of startups within this dataset. To account for the skewness and the wide range of magnitudes, I converted the total funding variable into a log variable giving $Logtotalfunding_{jt}$. Therefore, this study uses $Logtotalfunding_{jt}$ as one of the control variables for the analysis.

$Invyear_{jt}$. Further, I include the investment year dummies at which the VCs invest into startup j at investment year t. Existing literature find that controlling for investment year considers the possibilities that investments made in a particular year may have faced more turbulent conditions and that investments made in recent years may have different survival rates then investments made in older years (Dimov and De Clercq, 2006). I argue that these turbulences may affect the rate of investments made by venture capitals, both FVCs and CVCs. For instance, as observed in Table 2, there is a slight decrease in syndicate investments in 2008-2009 from 11 syndicates to 7 syndicates. This may be resulted from the 2008 financial crisis leading to negative lagged effects as seen in 2009. Hence, to control for these time effects, I decide to use investment year dummies.

$VEICindustrycode_t$. Lastly, I control the sub-industry differences of the startup j within the dataset by using the VEIC number as the industry classification (see Appendix, table A2). This data source's industry-specific coding scheme is an important factor to consider. VEIC stands for Startup Economics Industry Classification. As opposed to SIC/NAICS (Standard Industrial

Classification/North American Industry Classification System) codes used in corporate diversification studies, VEIC are used to represent sub-industries in the Refinitiv Eikon database. Like the NAICS system, VEIC codes are set up so that the numerical distance between them indicates how closely connected different industries are to one another. The VEIC method, however, groups "non-high tech" startups into fewer codes, hence in certain circumstances, the VEIC mapping may not capture strategic similarities or differences across industries (Matusik and Matiza, 2012). Contrarily, this method offers a more precise categorization for some technology-intensive startups such as computer software startups, particularly those that are frequently funded by VC capital. The reason to control for sub-industry differences is that each sub-industry has their own capabilities in attracting VC investments. Startups are more prone to turn to secrecy in sectors where patent protection is poor. Even if an innovation is patented in such fields, a company might not want to reveal it. Additionally, it is costly to protect a patent's rights (Lerner, 1995). Hence, this may lead to startups within sectors that have poor patent protection to be less incline to cooperate with VCs as they would have to reveal their patents leading to less. Theoretically, this leads to poor exit probability as these startups are less likely to be invested by VC syndicates. To control for such confounding effects, I include $VEICindustrycode_t$ as one of the control variables in this study.

3.3 Descriptive Statistics

Table 2 shows the descriptive statistics of US computer software startups invested by IVCs, CVCs and FVCs during the 2000-2023 period. As for the exit probability, there are only 24.3% of startups that have exited the market within the dataset. In terms of investment and syndication, the low mean magnitude indicates that FVCs and CVCs are not as prominent in investing in general or investing in syndicates relative to IVCs. More explicitly, 1060 (8.8%) observations have at least one CVC as their investors, 2244 (18.5%) have at least one FVC as their investor, and 8794 (72.7%) observations are invested only by an IVC. Clearly, it can be inferred that IVCs strongly dominate the investments within the technology software sector. Figure 2 supports this view that IVCs strongly dominate with the highest count of investments throughout the 2000-2023 investment period, followed by FVCs and lastly, CVCs. Likewise, syndication also shows that IVC syndicates dominate the number of syndications with 6534 (54%) observations, followed by 3292

(27.2%) startups with no syndication, 1356 (11.2%) startups with FVC syndicates and lastly, 916 (7.6%) startups with CVC syndication.

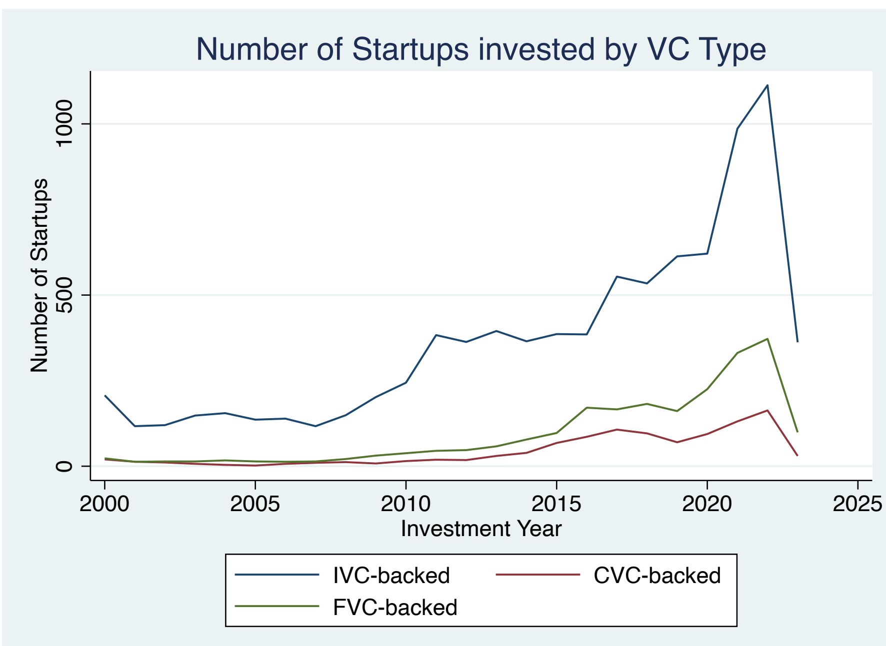
Table 2 Descriptive Statistics of US-based startups characteristics from 2000 to 2023

Variable	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
stage	12,098	2.522	0.824	1	4
exit	12,098	0.243	0.429	0	1
IVC_backed	12,098	0.727	0.446	0	1
FVC_backed	12,098	0.185	0.389	0	1
CVC_backed	12,098	0.088	0.283	0	1
IVC_syn	12,098	0.540	0.498	0	1
FVC_syn	12,098	0.112	0.315	0	1
CVC_syn	12,098	0.076	0.265	0	1
syndicatesize	12,098	3.291	2.309	1	12
rnumber	12,098	2.169	1.738	1	10
age	12,098	10.919	6.845	0	33
logtotalfunding	12,098	16.619	1.820	6.802	23.154

Figures 2 and 3 show a detailed overview of the distribution of startup investments and the exit status based on the type of syndication. It can be observed that IVC funding is the most popular type of funding by a great margin especially after 2020 whereby there are more than 1000 startups backed solely by IVCs. Whereas there are only less than 500 startups backed by FVCs and CVCs. In addition, FVC funding is more popular relative to CVC funding throughout the 23-year period. Interestingly, figure 3 show that startups are frequently invested within the early stage of development by all types of VCs with the greatest investment coming in from IVCs. It is important to highlight that this first glance on the distribution finding is not a surprise since it is aligned with existing literature indicating that FVCs and CVCs tend to invest in later stages relative to IVCs (Fulghieri and Sevilir, 2009; Dushnitsky and Shapira, 2010; Dai et al., 2012). Moreover, the number of VCs investing decreases as the stage of development increases, except for the seed stage since seed staged startups receive the least number of investments from VCs. It would be interesting how the significance of this distribution holds for each type of VC. As for the control variables, the low standard deviations are noticeable reflecting back to the similar characteristics of startups operating within the software technology industry. In terms of syndication and exit, figure 4 indicates that less than 5000 IVC-syndicate backed startups did not exit and only less than 2000 IVC-syndicate backed startups exit. Similarly, FVC-syndicate and CVC-syndicate backed startups also portray more non-exits. However, the difference is not as large and significant as the IVC-syndicate backed startups. Specifically, there are more than 1000 FVC-syndicate backed startups and around 800 CVC-backed startups that did not exit. On the other hand, there were less than 500 startups that exited which were backed by FVC and CVC syndicates.

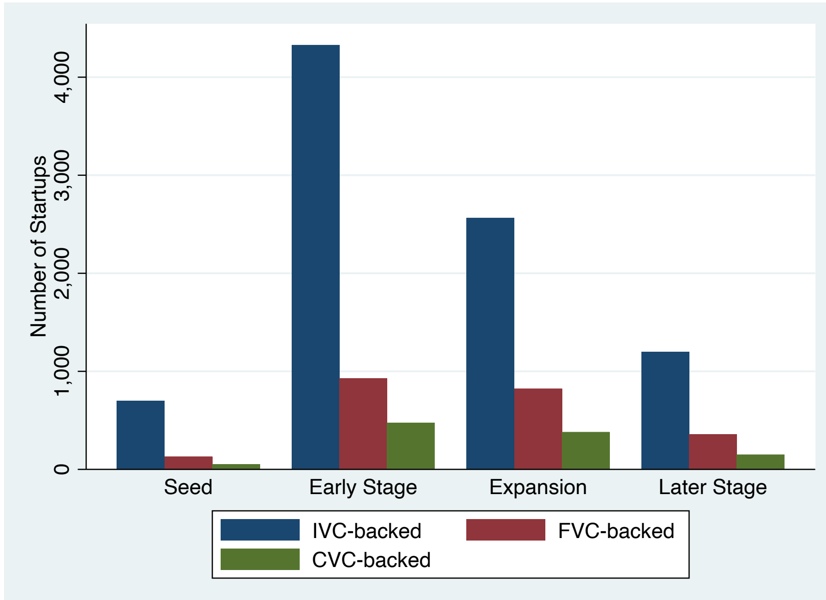
Overall, we can conclude that the dataset is heavily skewed with most of the startups are backed by IVCs. In terms of data pattern, there is a sudden surge in investment prevalence for startups backed by IVCs after the 2020s. Moreover, most of the startups are invested within the early stage of development. In terms of syndication and exit, most of the startups did not exit with the highest difference coming from IVC-syndicate backed startups. Interesting to see whether this first glance of distribution hold significantly within the analysis for hypothesis 1 and 2.

Figure 2 Number of Startups invested per year by type of VC



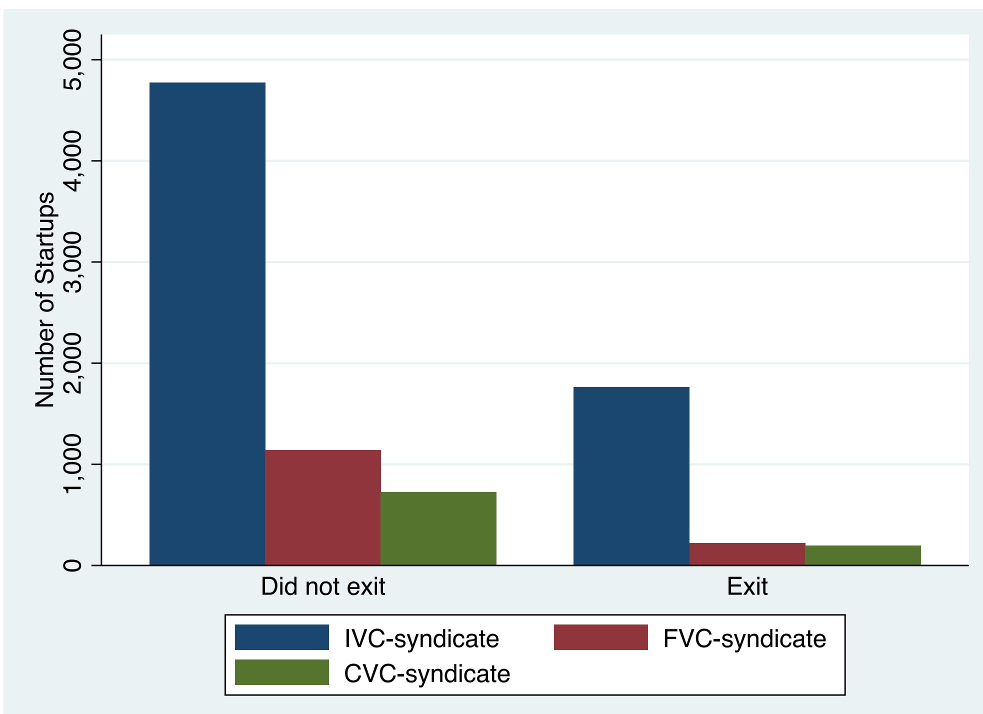
Note. Figure 2 depicts the number of startups invested over the 23-year period. IVC-backed startups are the most prevalent type of investment followed by startups backed by FVCs and then, CVCs. Important to note that there is a sudden surge in startups being invested by IVCs after 2020.

Figure 3 Number of Startups by stage of development



Note. IVC-backed startups dominate throughout the development stages with the highest for startups within the early stage followed by startups backed by FVCs and then, CVCs.

Figure 4 Distribution of exit status based on the type of syndication



Note. Most of the syndicate backed startups did not exit. The highest difference in non-exit and exit is portrayed by IVC-syndicate backed startups followed by FVC syndicates and CVC syndicates.

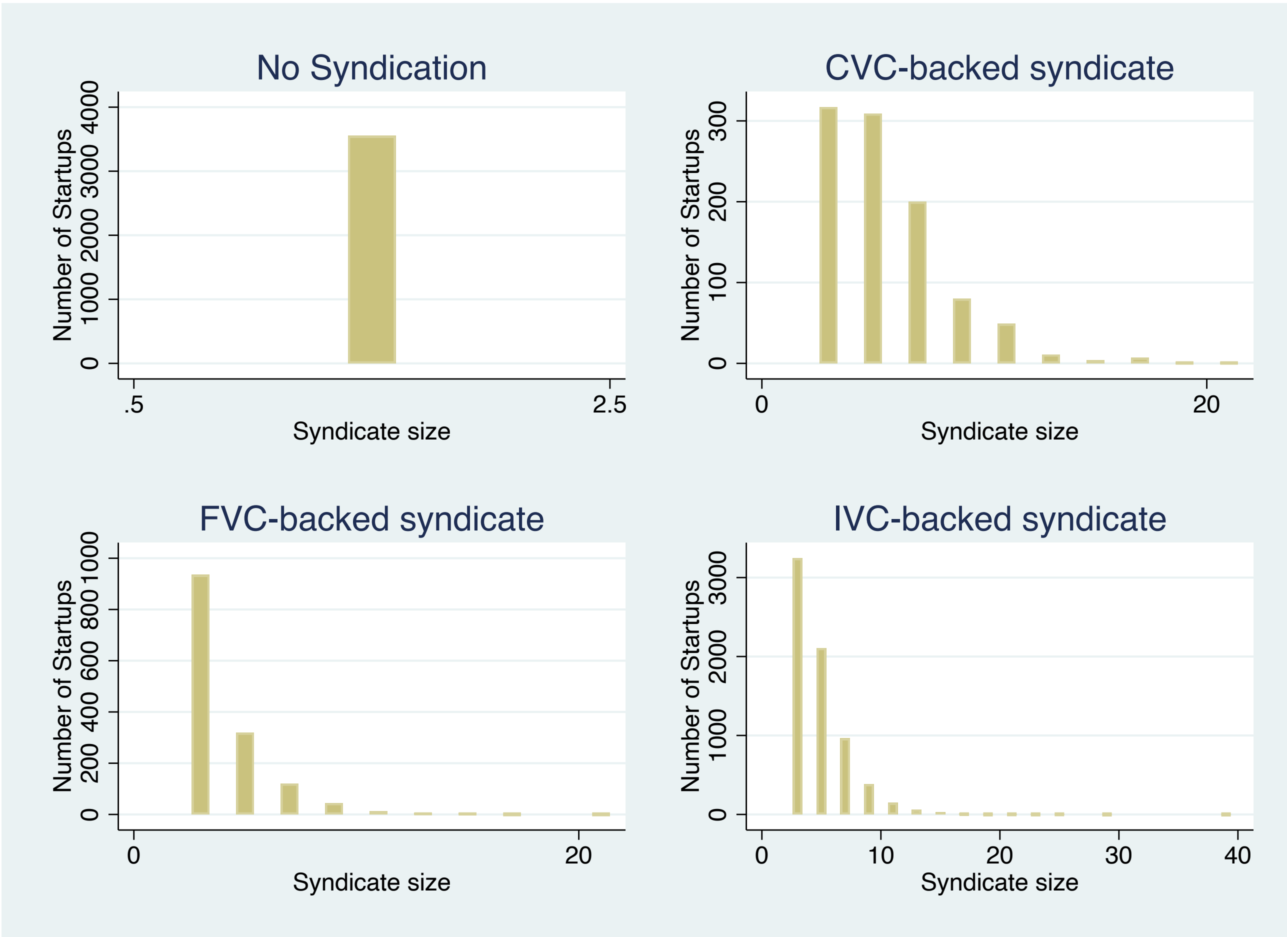
In terms of syndicate size, the descriptive statistics in Table 2 show that the average syndicate size is 3.291 investors within a syndicate which is at the lower end of the syndicate size spectrum. This indicates that having mid-size syndicate sizes (2-5 co-investors) are more common than having larger syndicates. With a maximum of 12 VCs investing within a syndicate, this shows that VCs within this dataset are less likely to be investing with multiple investors as aligned with Jääskeläinen et al. (2006) and Kim and Park (2011). More precisely, Table 3 show the syndicate size characteristics with respect to the type of syndication. The mean is equal to 3.369 for syndicates participated by IVCs only and 4.429 for syndicates participated with at least one CVC. Hence, CVC syndicates exhibit higher average syndicate participation. This is aligned with existing literature in the United States (Dushnitsky and Shapira, 2010) and Canada (Brander et al., 2002). Interestingly, the outlook is the opposite for FVC syndicates. FVC syndicates, on average, have 2.447 participants in a syndicate which is less than the average. The same finding was found by Dai and Nahata (2016) in which they found only 35% of syndicates with a foreign VC versus 59% for syndicates with local IVCs. Moreover, Figure 5 shows that each type of VC syndication follows a similar distribution where the number of VCs participating in the syndicated investments decline as the syndicate size increases.

Table 3 Syndicate size characteristics for each type of syndication

Variable	Number of Observations	Mean	Minimum	Maximum
IVC backed Syndicate Size	8794	3.369	1	12
FVC backed Syndicate Size	2244	2.447	1	12
CVC backed Syndicate Size	1060	4.429	1	12

Note. Important to notice that the maximum number is 12 for all three types of VCs due to removing the 99th percentile outliers. Including these datapoints could impede the accuracy of the regression results.

Figure 5 Syndicate Size Distribution by each type of VC



Note. Figure 5 shows the syndicate size distribution for each type of VC. In general, all VC types portray a negative trend as the syndicate size increases.

Moreover, it may be argued that the patterns of syndicate size merely reflect CVCs' and FVCs' preference for investing in established enterprises. That is, successive rounds sometimes demand for larger sums, and more VCs 'pitch in' as a result. To test this argument, I used the Mann-Whitney-Wilcoxon (MWW) nonparametric test, testing for the null hypothesis that IVC investments have similar syndicate sizes with FVC or CVC syndicate sizes. The same is tested for syndicates. I find that the syndicate size differences remain at each stage of development and significant at the 1% significance level (see Appendix, Table A3). In other words, controlling for the stage of development of a startup, I find that FVC syndicates have significantly less syndicate participants than similar stage rounds that are led by either CVC or IVC. On the other hand, CVC syndicates have significantly more syndicate participants than similar stage rounds in which are led by either FVC or IVC.

3.4 Model Specification

This study aims to look at the effects of FVC and CVC investments and syndicate investments using logistic regression methods. To investigate the first hypothesis, I use the ordered logit regression method since the dependent variable stage is a categorical variable that follows an ordinal nature. Specifically, it represents a natural ordering or progression of the development stages that a startup typically goes through. Each stage represents a distinct phase in the startup's development, with different characteristics, challenges, and funding requirements. The ordering of the stages implies that each subsequent stage encompasses the characteristics and requirements of the preceding stages while adding new elements specific to that stage. For instance, the expansion stage includes aspects of both the seed stage and early stage, but it also involves additional considerations related to scaling operations and entering new markets. To support this point of view, Dushnitsky and Shapira (2010) also recognize this as an ordinal variable as it is "built around a latent regression in the same manner as the binomial-logit model". Moreover, the ordered logit model assumes an ordinal logistic distribution for the dependent variable. Based on whether the startups are invested by an FVC or a CVC, the model can calculate the cumulative probabilities of the exit probability falling into several ordinal groups and the magnitude it fits for each relationship shows a general trend throughout the ordinal values of the dependent variable (Warner, 2008). Therefore, by using the ordered logit regression, I can account for the ordinal nature of the dependent variable, stage. I model the effect of startups being invested by a CVC or a FVC towards exit probability by each stage of development using separate models for each type of investment-

Hypothesis 1-

$$P(y = j \mid X_1, \dots, X_k) = \frac{exp\left(\tau_j - \beta_1 X_1 - \beta_2 X_2 \ldots - \beta_k X_k\right)}{1 + exp\left(\tau_j - \beta_1 X_1 - \beta_2 X_2 \ldots - \beta_k X_k\right)} - \frac{exp\ (\tau_{j-1} - \beta_1 X_1 - \beta_2 X_2 \ldots - \beta_k X_k)}{1 + exp\ (\tau_{j-1} - \beta_1 X_1 - \beta_2 X_2 \ldots - \beta_k X_k)}$$

Where j = seed, early, expansion, or later, representing the ordered stage of development y for a particular startup. X_1 represents the independent variable FVC_backed and X_2 represents the independent variable CVC_backed. X_k are all the control variables within the regression. τ_j is the threshold of the latent variable. β_1 and β_k are the coefficients of the independent variable and the control variables, respectively.

As for hypothesis 2 and 3, I use a logistic regression with a dichotomous variable exit as the dependent variable. Since exit may not be normally distributed, the logit method is utilized. Cox and Snell (1989) discuss two primary reasons for using logistic distribution. First, it is a very adaptable and simple function to utilize from a mathematical perspective. Second, the model's parameters serve as the foundation for accurate estimations. The specific logistic regression model that I use is-

Hypothesis 2-

$$E(Y|x) = \frac{exp\ (\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_k X_k)}{1 + exp\ (\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_k X_k)}$$

Where Y is the binary variable exit, X_1 is the independent variable IVC_syn, X_2 represents the FVC_syn, and X_3 represents the CVC_syn, and X_k are all the other relevant control variables. Moreover, the hypothesis 3 model also uses exit as the dependent variable Y. In this case, I regress three separate models for each type of syndication. X_1 represents the independent variable IVC_syn, X_2 represents the FVC_syn, and X_3 represents the CVC_syn. Moreover, X_4 represents syndicate size. Furthermore, the standard errors of all the three hypotheses are clustered at firm level.

Hypothesis 3-

$$E(Y|x) = \frac{exp\ (\beta_0 + \beta_1 X_1 + \beta_2 X_4 + \beta_3 X_1 X_4 + \ldots + \beta_k X_k)}{1 + exp\ (\beta_0 + \beta_1 X_1 + \beta_2 X_4 + \beta_3 X_1 X_4 + \ldots + \beta_k X_k)}$$

$$E(Y|x) = \frac{exp\ (\beta_0 + \beta_1 X_2 + \beta_2 X_4 + \beta_3 X_2 X_4 + \ldots + \beta_k X_k)}{1 + exp\ (\beta_0 + \beta_1 X_2 + \beta_2 X_4 + \beta_3 X_2 X_4 + \ldots + \beta_k X_k)}$$

$$E(Y|x) = \frac{exp\ (\beta_0 + \beta_1 X_3 + \beta_2 X_4 + \beta_3 X_3 X_4 + \ldots + \beta_k X_k)}{1 + exp\ (\beta_0 + \beta_1 X_3 + \beta_2 X_4 + \beta_3 X_3 X_4 + \ldots + \beta_k X_k)}$$

4 Results and Discussion

In the following, the average marginal effects of the logit models are presented and interpreted based on their sign, significance, and magnitude. Table 3 shows the results for Hypothesis 1, Table 4 presents the results for Hypothesis 2, and Table 5 depicts the results for Hypothesis 3.

4.1 Hypothesis 1

Table 3 presents the average marginal effects for the dependent variable stage and the investment period 2000-2023. Hypothesis 1 proposes both foreign (FVC) and corporate venture capital (CVC) investments are more likely to occur for startups at the later stage of startup development relative to a startup invested only by an IVC. Hence, the effect of being invested by FVCs and CVCs are expected to be higher for the expansion or later stage of startup development relative to Seed or Early stage of development.

Referring to Table 4, I controlled for the investment year and industry differences. On average, an FVC backed startup is less likely to be invested in the seed stage by 0.6 percentage points relative to an all-IVC backed startup, ceteris paribus. This effect is statistically significant at the 5% significance level. Similarly, when looking at the probability of being invested at the early stage, on average, the probability to be invested in the early stage for an FVC backed startup is 0.5 percentage points lower relative to an all-IVC backed startup, ceteris paribus. This effect is statistically significant at the 5% significance level. Interestingly, relative to seed and early stage, I observe significantly different outcomes for the probability of startups being invested in the expansion and later stage. On average, the probability to be invested in the expansion stage for an FVC backed startup is 0.6 percentage points higher relative to all-IVC backed startups, ceteris paribus. This effect is statistically significant at the 5% significance level. Later stage startups have a similar effect with expansion staged startups with a lower magnitude. Specifically, on average, an FVC backed startup is more likely to be invested in the expansion stage by 0.6 percentage points relative to startups invested only by IVCs. This effect is statistically significant at the 5% significance level. These findings are in line with existing literature showing that FVCs are more likely to invest in less informationally opaque startups (Dai et al., 2012). Potential reasons why are offered in the literature such as cultural (Moore et al., 2015) and spatial distances (Dai et al., 2012). These institutional differences cause additional problems for FVCs leading to risks of adopting new organizational policies and practices (Kostova and Roth, 2002) and difficulty in realizing intended strategies (Dobrev and Carroll, 2003). The second row in table 3 shows the results for CVC backed startups. Interestingly, CVC backed startups do not portray any significant results for all stages of development relative to all-IVC backed startups.

Overall, although FVC backed startups exhibit significant positive results for the expansion and later stage, the CVC backed startups do not portray any significant results. Hence, I could not fully conclude that the results support hypothesis 1. Therefore, I partially reject hypothesis 1.

Table 4 Average Marginal Effects of startup stage of development for Computer Software startups invested by FVCs and CVCs for the 2000-2023 investment period.

Variable	Seed	Early	Expansion	Later
FVC_backed	-0.006**	-0.005**	0.006**	0.004**
	(0.003)	(0.002)	(0.003	(0.002)
CVC_backed	-0.001	-0.000	0.001	0.000
	(0.004)	(0.003)	(0.004)	(0.003)
rnumber	-0.021***	-0.017***	0.023***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)
logtotalfunding	-0.005***	-0.004***	0.005***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
age	-0.056***	-0.046***	0.061***	0.040***
	(0.002)	(0.001)	(0.001)	(0.001)
Investment year dummies	YES	YES	YES	YES
Sub-industry dummies	YES	YES	YES	YES
Log probability	-7336.821	-7336.821	-7336.821	-7336.821
R-squared value	0.488	0.488	0.488	0.488

Note. Standard errors in parantheses. The dependent variable is the stage of development of the startup. The independent variable FVC_backed represents startups invested by at least one FVC and CVC_backed represents startups invested by at least one CVC. The reference category is IVC_backed representing invested startups only invested by IVCs. The number of observations is 12,098 startups. The ordered logit regression in which the average marginal effects table was derived from has a log-probability value of -7336.821 and an R-squared value of 0.488. ***p-value < 0.01, **p-value < 0.05, *p-value < 0.1

4.2 Hypothesis 2

Table 4 showcases the average marginal effects for the dummy dependent variable exit within the investment period 2000-2023. Hypothesis 2 proposes both foreign (FVC) and corporate venture capital (CVC) would positively affect the exit probability of startups relative to no syndication.

Looking at Table 5, after controlling for investment year and industry differences, I can infer that on average, IVC-backed syndicate startups increase the probability to exit by 31.5 percentage points relative to startups invested with no syndication. This effect is statistically significant at the 1% significance level. Moreover, the second row of Model 2 shows the effect of FVC-backed syndicate investments on exit probability. On average, FVC-backed syndicate startups increase the probability to exit by 2.3 percentage points relative to startups invested with no syndication. However, this effect is statistically insignificant at the 10% significance level. Lastly, the third row of Model 2 depicts the effect of startups invested by a CVC-backed syndicate. On average, CVC-backed syndicate startups increase the probability to exit by 37.4 percentage points relative to startups invested with no syndication. This effect is statistically significant at the 1% significance level. From this result, it is important to highlight that CVC-backed syndicates have a higher exit probability relative to IVC-backed syndicates with a 5.9% exit probability difference. This finding is in line with previous studies analysing the CVC syndicates (Gompers and Lerner, 1998; Dushnitsky and Lenox, 2006; Chemmanur et al., 2012) where CVC-backed syndicates with strategic intentions are more likely to exit rather than financially driven IVC syndicates (Gompers and Lerner, 1998).

Overall, I can conclude for hypothesis 2 that although CVC-backed syndicates depict a significant positive result towards the probability to exit, the FVC-backed syndicates do not portray any significant results. Hence, I could not fully conclude that the results support hypothesis 2. Likewise with hypothesis 1, I partially reject hypothesis 2.

Table 5 Average Marginal Effects of Exit Probability for FVC and CVC syndicate investments based on the Logit Regression for Computer Software Startups for the investment period 2000-2023

Variable	Exit Probability
IVC_syn	0.315***
	(0.061)
FVC_syn	0.023
	(0.105)
CVC_syn	0.374***
	(0.108)
rnumber	0.141***
	(0.017)
logtotalfunding	0.024
	(0.019)
age	0.028***
	(0.009)
Investment Year dummies	YES
Sub-industry dummies	YES
Number of Observations	12098
Log-probability	-4628.5559
R-squared value	0.271

Note. Standard errors in parantheses. The dependent variable is the exit status of the startup. The independent variable IVC_syn represents startups invested by IVC syndicates, FVC_syn represents startups invested by FVC syndicates and CVC_syn represents startups invested by CVC syndicates. The reference category is startups with no syndication. ***p-value < 0.01, **p-value < 0.05, *p-value < 0.1

4.3 Hypothesis 3

Regarding H3, Figure 6 shows the scatterplot of conditional marginal effects on exit probability at different syndicate sizes for different types of VC syndicates within the 2000-2023 investment period. Hypothesis 3 proposes that the syndicate size of an investment round will negatively moderate the relationship between the foreign or corporate venture capital syndicate and the exit probability of a startup.

By going through Figure 6, we observe three different lines of exit probability conditional on syndicate size. The blue line represents the FVC-backed syndicates, the red line represents the CVC-backed syndicates, and the green line represents IVC-backed syndicates. Before we deep dive into the figure, it is important to remember that it is required at least two investors to be considered a syndicate. Hence, for syndicate size equal to 1, I consider this as a startup invested by a sole investor and not a syndicate. From Figure 6, we can deduce that both IVC and CVC backed syndicate lines portray a negative trend where the greater the syndicate size of the startup, the less the expected probability for the startup to exit. Table 6 depicts the conditional marginal effects of exit probability for various syndicate sizes categorized by each type of VC syndication. Interestingly, CVC-backed syndicates indicate a significant effect towards exit probability only at the first two and last three extreme points of the syndicate size spectrum towards exit probability. Specifically, CVC-backed syndicates depict decreasing positive effects at syndicate sizes 2-3 and negative effects at syndicate sizes 10-12. For instance, startups invested by a CVC syndicate increases the exit probability by 3.2 percentage points relative to startups invested with no syndication for startups with a 3-sized syndicate. These effects are statistically significant at the 10% significance level. Additionally, IVC-backed syndicates indicate a decreasing positive effect towards exit probability for all syndicate sizes except for syndicate size 12 where the exit probability magnitude eventually become negative. However, the effect is highly significant at the smaller syndicate sizes and gradually the significance fades out as the syndicate size increases. Specifically, the effect is significant at least at the 10% significance level for syndicate sizes 1-5. In contrast, FVC-backed syndicates portray a positive trend. Looking closely at FVC-backed invested syndicates, although it portrays a positive trend, we see that the probability to exit is negative for all syndicate sizes and the negative effect decreases as the syndicate size increases. This is an interesting finding as it conflicts with the existing literature point of view. Theoretically, the positive trend outlined by the FVC syndicates indicate that the resource-based benefits such as knowledge and monitoring capabilities (Kim and Park, 2021) and financial funding (Zhang, Gupta, and Hallen, 2017) outweigh the coordination costs of syndication. Another possible explanation is that although FVCs do experience a lot of culture conflict with other IVCs within their respective syndicate, FVCs evaluate potential investments more thoroughly before investing in their portfolio startups because they anticipate cultural differences (Nahata et al., 2014). Before investing into the US technology market, FVCs may anticipate challenges that might arise due to cultural differences and careful selection of these startups boosts the probability of exiting the market. However, this effect is significant at least at

10% significance level only for syndicate sizes 2 until 4. Hence, I could not fully conclude the positive trend for all syndicate sizes. Moreover, the standard errors increase as the syndicate size increase due to the decreasing number of observations. This results in the coefficients to be even less significant as the syndicate size increases.

Overall, I conclude that although FVC and CVC-backed syndicates portray significant negative effects towards exit probability for several syndicate sizes, the effect does not hold any significant results for most of the syndicate sizes. Additionally, as opposed to existing literature and my hypothesis, FVC-backed syndicate investments portray a positive effect. Hence, I am not able to fully accept hypothesis 3. With that being said, I conclude that I partially reject hypothesis 3.

Figure 6 Scatterplot of Conditional Marginal Effects at different syndicate sizes on exit probability

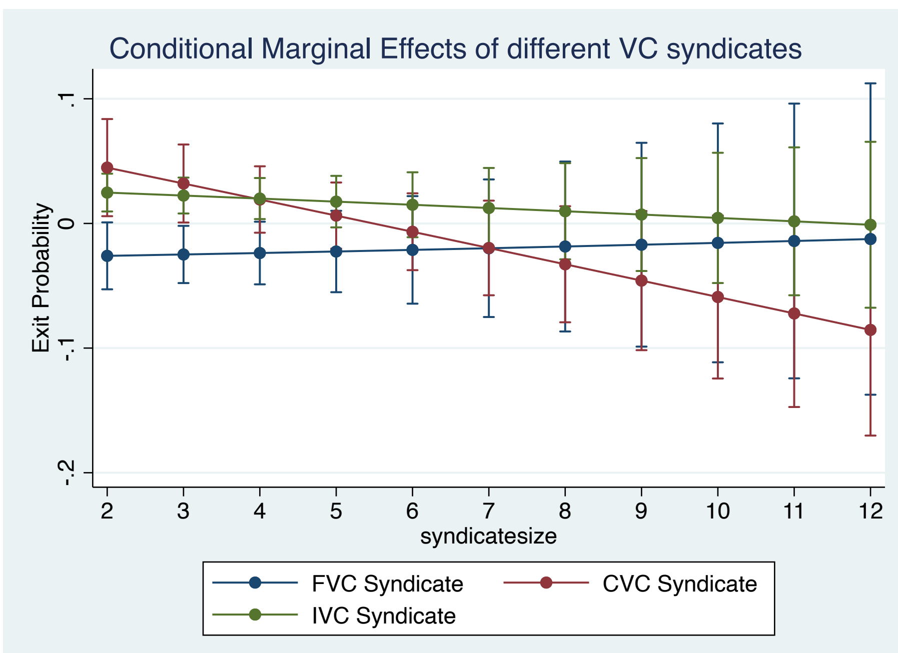


Table 6 Conditional Marginal effects of exit probability for various syndicate size

Syndicate Size	FVC Syndicate	CVC Syndicate	IVC Syndicate
2	-0.026*	0.045**	0.025***
	(0.014)	(0.020)	(0.008)
3	-0.025**	0.032**	0.022***
	(0.012)	(0.016)	(0.007)
4	-0.024*	0.019	0.020**
	(0.013)	(0.014)	(0.008)
5	-0.022	0.006	0.017*
	(0.017)	(0.014)	(0.011)
6	-0.021	-0.007	0.015
	(0.022)	(0.016)	(0.013)
7	-0.020	-0.020	0.012
	(0.028)	(0.019)	(0.016)
8	-0.019	-0.033	0.010
	(0.035)	(0.024)	(0.020)
9	-0.017	-0.046	0.007
	(0.042)	(0.028)	(0.023)
10	-0.016	-0.059*	0.004
	(0.049)	(0.033)	(0.027)
11	-0.014	-0.072*	0.002
	(0.056)	(0.038)	(0.030)
12	-0.013	-0.085**	-0.001
	(0.064)	(0.043)	(0.034)

Note. Standard errors in parantheses. The dependent variable is the exit status of the startup. The independent variable IVC_syn represents startups invested by IVC syndicates, FVC_syn represents startups invested by FVC syndicates and CVC_syn represents startups invested by CVC syndicates. The reference category is startups with no syndication. ***p-value < 0.01, **p-value < 0.05, *p-value < 0.1

5 Robustness Checks

To check the credibility of the results, I ran several alternative regressions with different samples and different variables.

5.1 Robustness Check 1: Accounting for Investment Years with Economic Crisis

One potential concern that may affect the validity of the results is that several investment years may affect the investment and exit probability of a startup. Specifically, during times of economic crises in which economic activity is uncertain affecting investment activities. Bellavitis et al. (2021) assesses the effect of the COVID-19 pandemic towards VC investments. They find a significant decline in VC investments in over 130 countries during the pandemic. Interestingly, the decline was more pronounced in seed-stage startups. Similarly, De Vries and Block (2011) find that, during the 2000-2001 dot-com crisis and 2008-2009 financial crisis, VCs had a lower tendency to syndicate their investments and that the size of the syndicates were smaller. A reason being that the quantity of capital going into the VC market drastically decrease during times of economic crisis leading to fewer possibilities to exit successful start-ups (De Vries and Block, 2011). Hence, previous literature indicates years with severe economic crisis have an impact towards VC investments and can definitely impede the accuracy of the results in this study.

Looking at my dataset, I decide to do a pre-, during- and post-analysis surrounding the 2008-2009 financial crisis. Despite the 20 investment year data availability, the reason for only using the 2008-2009 financial crisis is due to the centrality of the 2008-2009 financial crisis within the dataset. Specifically, there is sufficient data to analyze the pre and post effects of the financial crisis since the 2008-2009 investment years are positioned somewhat in the middle of the dataset.

5.1.1 Hypothesis 1 - Accounting for Investment Years with Economic Crisis

The results for hypothesis 1 show different results for each of the investment periods. Table 7 shows the average marginal effects of startups invested by an FVC and a CVC towards the stage of development of the startup before the financial crisis. Interestingly, Table 7 indicates that FVCs are more likely to invest in expansion and later stages relative to seed and early stages with more than 4 times the magnitude of the main results. For instance, on average, an FVC backed startup is less likely to be invested in the expansion stage by 2.8 percentage points relative to an all-IVC backed startup, ceteris paribus. The effect is statistically significant at the 10% significance level. A possible explanation for the large increase in magnitude would be due to the highly information opaqueness of the computer software startups between 2000 and 2007 investment years relative to more recent years in which public investment information about the industry peers are more accessible (Gibbons, 2023). Another possible explanation would be that the computer-related industry itself tend to have a greater level of information asymmetry and uncertainty (Dai et al., 2012). Similarly, Dai et al. (2012) find that FVCs are 16-27% less interested in investing in seed and early stages for the computer-related startups during the 1996-2006 investment years. Moreover, results for investment years during the financial crisis report insignificant results and results for investment years after the financial crisis report consistent results with the main results (see Appendix, table A8 and A9). The only difference is that the effect is stronger with a 1% significance level for FVC backed startups. Nevertheless, consistent with the main results, hypothesis 1 is partially rejected.

Table 7 Average Marginal Effects of startup stage of development for Computer Software startups invested by FVCs and CVCs before the 2008-2009 financial crisis

Variable	Seed	Early	Expansion	Later
FVC_backed	-0.026*	-0.040*	0.028*	0.039*
	(0.001)	(0.021)	(0.015)	(0.021)
CVC_backed	-0.004	-0.006	0.004	0.006
	(0.013)	(0.020)	(0.014)	(0.020)
rnumber	-0.032***	-0.048***	0.033***	0.047***
	(0.004)	(0.005)	(0.004)	(0.004)
logtotalfunding	-0.015***	-0.023***	0.016***	0.022***
	(0.004)	(0.005)	(0.004)	(0.005)
age	-0.023***	-0.034***	0.024***	0.033***
	(0.002)	(0.002)	(0.002)	(0.002)
Investment year dummies	YES	YES	YES	YES
Sub-industry dummies	YES	YES	YES	YES
Log probability	-1253.844	-1253.844	-1253.844	-1253.844
R-squared value	0.240	0.240	0.240	0.240

Note. Standard errors in parantheses. The dependent variable is the stage of development of the startup. The independent variable FVC_backed represents startups invested by at least one FVC and CVC_backed represents startups invested by at least one CVC. The reference category is IVC_backed representing invested startups only invested by IVCs. The number of observations is 1335 startups. The ordered logit regression in which the average marginal effects table was derived from has a log-probability value of -1253.8442 and an R-squared value of 0.2395. ***p-value < 0.01, **p-value < 0.05, *p-value < 0.1

5.1.2 Hypothesis 2 - Accounting for Investment Years with Economic Crisis

Regarding hypothesis 2, the results portray generally consistent results with the main results (see Appendix, table A10). Specifically, there are no significant differences in terms of sign and significance. The average marginal effects results before the financial crisis report less significant effects for IVC syndicates relative to the main result. Additionally, the coefficient of CVC syndicates is insignificant towards the exit probability. Moreover, the model with a dataset during the financial crisis report insignificant coefficients and the post financial crisis model report results consistent with the main results. Overall, hypothesis 2 is partially rejected.

5.1.3 Hypothesis 3 - Accounting for Investment Years with Economic Crisis

Regarding hypothesis 3, the results generally do not portray any significant differences relative to the main results. Both conditional marginal effect coefficients for the models before and during financial crisis depict insignificant results (see Appendix, Table A11 and A12). On the other hand, the conditional marginal effect coefficients after the financial crisis are consistent with the main results (see Appendix, Table A13). However, the negative effects of CVC syndicate sizes 10-12 are insignificant. This indicates for observations after the 2008-2009 financial crisis, CVCs that invest in smaller syndicates increases the probability for the startup to exit. Moreover, similar with the main results, the confidence interval increases as the syndicate size increases. Overall, even though the coefficients of the various types of syndicate sizes are insignificant, there are no significant changes in the sign and magnitude. Hence, hypothesis 3 is partially rejected after accounting for investment years with economic crisis.

5.2 Robustness Check 2: Different Exit types

Secondly, the results of hypotheses 2 and 3 may differ depending on the exit type the startup experiences. Specifically, Refinitiv Eikon shows that there are three main different types of exits that startups experience within this dataset: i) Mergers and Acquisitions (M&A), ii) Leveraged Buyout (LBO) and iii) Initial Public Offering (IPO). Therefore, for this robustness check, I created three dummy variables for startups experiencing an M&A, LBO or an IPO, respectively.

5.2.1 Hypothesis 2 – Different Exit types

After replacing the Exit variable with the specific types of exits (M&A, LBO, and IPO) as the dependent variable, the results in Table 8 suggest that, for an M&A exit type, the coefficients have the same signs and significance although the magnitude increased slightly. On the other hand, LBO and IPO startups have drastically different coefficients relative to the main results. Startups that exited via an LBO have insignificant coefficients while IPO exit types report insignificant coefficients except for FVC syndicates. Specifically, on average, startups invested by FVC syndicates are less likely to go public by 66.9 percentage points relative to startups invested with no syndication. This effect is statistically significant at the 5% significance level. This finding is in contrast with existing literature (Cumming et al., 2016; Bertoni et al., 2014).

Table 8 Average Marginal Effects of different types of exits for various syndication type

Variable	M&A	LBO	IPO
IVC_syn	0.426***	-0.342	-0.162
	(0.063)	(0.217)	(0.176)
FVC_syn	0.137	0.091	-0.669**
	(0.107)	(0.336)	(0.335)
CVC_syn	0.491***	0.182	-0.416
	(0.111)	(0.385)	(0.306)
rnumber	0.119***	0.012	0.105***
	(0.017)	(0.042)	(0.036)
logtotalfunding	-0.122***	0.288***	1.085***
	(0.018)	(0.075)	(0.077)
age	0.017*	0.100***	0.041*
	(0.010)	(0.022)	(0.025)
Sub-industry dummies	YES	YES	YES
Investment Year dummies	YES	YES	YES
Observations	12,098	12,098	12,098

Note. Robust standard errors in parantheses. The dependent variable is the exit status of the startup. The independent variable IVC_syn represents startups invested by IVC syndicates, FVC_syn represents startups invested by FVC syndicates and CVC_syn represents startups invested by CVC syndicates. The reference category is startups with no syndication. ***p-value < 0.01, **p-value < 0.05, *p-value < 0.1

A potential reason for the negative effect includes the difference in cultural and geographic characteristics between the startups, IVcs, and the FVCs leading to higher chances of conflict less effective in monitoring and selection (Dai et al., 2012). In support with this, existing literature also finds that FVC backed startups are less likely to exit via an IPO if the institutional differences are too high (Moore et al., 2015) which may lead to conflict and unrealized intended strategies (Dobrev and Carroll, 2003). In other words, the coordination costs of having an FVC participating within a syndicate overcomes the resource-based benefits leading to a negative net effect. Moreover, it is important to point out that these effects may be derived by the distribution of the data. Specifically, a certain exit type may be more frequent relative to other exit types. Table 9 depicts a detailed overview of the current startup exit status. Within this table, I observe that Merger and Acquisition is the most popular exit type accounting 21.01 percent of the total observations. It is also important to point out that most of the startups within this dataset have not exited the market and these startups are labeled as active accounting for 75.67 percent of the dataset. Therefore, in terms of startup status, the dataset is highly skewed. Overall, other than the FVC syndicate invested startups that exited via an IPO, I can conclude that my results are robust to different types of exits. Therefore, hypothesis 2 is partially rejected.

Table 9 Detailed overview of startup status

Startup Status	Frequency	Percentage
Merger and Acquisition	2,542	21.01
Active	9,155	75.67
LBO	139	1.15
IPO	262	2.17
Total	12,098	100.00

5.2.2 Hypothesis 3 – Different Exit types

Regarding hypothesis 3, except for the M&A exit type, there are generally several differences being portrayed within each type of exit relative to the main results. Regarding the conditional marginal effects of exiting via an M&A for various syndicate sizes, relative to the main results, the only difference is that the negative effect is greater and more significant at larger syndicate sizes for startups invested by CVC syndicates (see Appendix, Table A14). A possible explanation for this would be that the coordination costs are more prominent for CVC syndicates at larger syndicate sizes (Hellmann et al., 2008; Chemmanur et al., 2011). Other than that, FVC syndicates are also insignificant towards exiting via an M&A and the positive effect is more significant for IVC syndicates at lower syndicate size. Regarding the general trend of the effect, the scatterplot of conditional marginal effects on exiting via an M&A for various syndicate sizes show that there are no significant differences relative to the main results in terms of sign, significance and magnitude (see Appendix, Figure A5). Similar to the main results, the standard errors of each syndicate size coefficient also increase as the syndicate size increases resulting in a larger confidence interval for all exit types. Moreover, other exit types portray mostly insignificant coefficients (see Appendix, Tables A15 and A16). Likewise with hypothesis 2, this is mainly driven by the skewness of the data in which there are less observations both for LBO and IPO relative to M&A. Nevertheless, at least for startups exited via an M&A, the effects portrayed are consistent with the main results. Hence, after replacing the dependent variable with various exit types, hypothesis 3 is still partially rejected.

5.3 Robustness Check 3: Midsize Syndicates

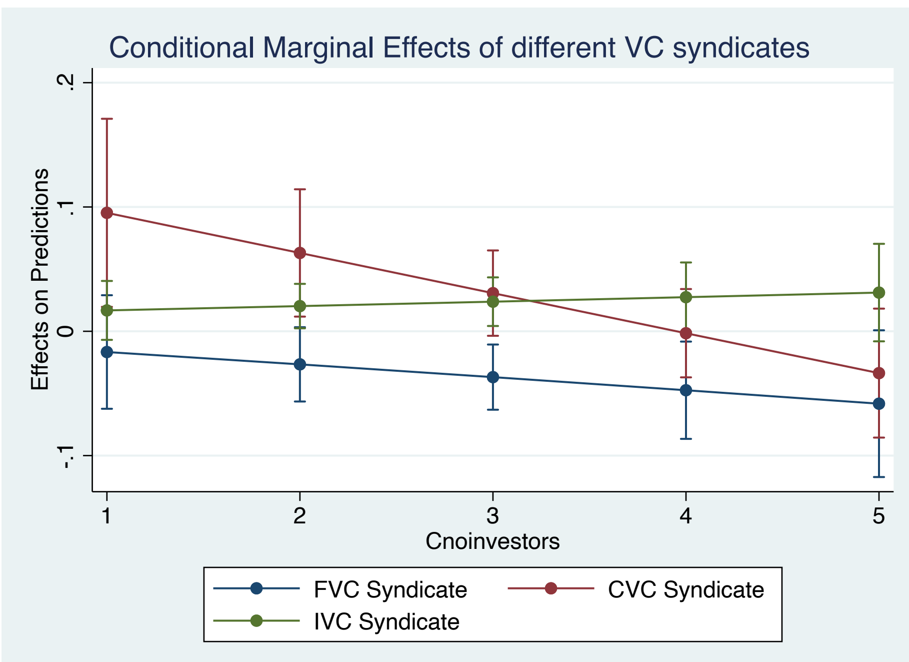
Moreover, to ensure that the results are not driven by relatively few rounds containing a large number of VCs (Zhang et al., 2017), I also conducted an analysis restricting my sample to investment rounds characterized by midsize syndicates (i.e., containing only 2-5 investors). After only including startups invested by VCs with midsize syndicates, specifically for hypothesis 1 and 2, I find that the results are consistent with the main results in terms of sign and magnitude size of the coefficient (see Appendix, Tables A17 and A18). Therefore, after only considering startups invested by midsize syndicates, hypotheses 1 and 2 are only partially rejected. Interestingly, for hypothesis 3, I find a slight difference in the syndicate size trend. Specifically, Table 10 and Figure 7 show that FVC syndicates portray a significant negative trend contrasting the main results which posits a positive trend. The effect is statistically significant at the 10% significance level. On top of that, IVC syndicates portray a significant positive trend contrasting the main results which posit a negative trend. This shows that a few rounds with a large number of investors have a definite impact towards the exit probability on various syndicate sizes. Additionally, unlike the main results, the standard errors are relatively small resulting a significant effect relative to the main results. Therefore, for startups invested by midsize syndicates, hypothesis 3 is partially rejected.

Table 10 Conditional Marginal effects of exit probability for midsize syndicates

Syndicate Size	FVC Syndicate	CVC Syndicate	IVC Syndicate
2	-0.027*	0.063**	0.020**
	(0.015)	(0.026)	(0.009)
3	-0.037***	0.031*	0.024**
	(0.013)	(0.018)	(0.010)
4	-0.047**	-0.002	0.027*
	(0.020)	(0.018)	(0.014)
5	-0.058*	-0.034	0.031
	(0.030)	(0.026)	(0.020)

Note. Robust standard errors in parantheses. The dependent variable is the exit status of the startup. The independent variable IVC_syn represents startups invested by IVC syndicates, FVC_syn represents startups invested by FVC syndicates and CVC_syn represents startups invested by CVC syndicates. The reference category is startups with no syndication. ***p-value < 0.01, **p-value < 0.05, *p-value < 0.1

Figure 7 Scatterplot of Conditional Marginal Effects for midsize syndicate invested startups at various syndicate sizes on exit probability



5.4 Robustness Check 4: Including round number and syndicate size outliers

Knowing that the main analysis within this study removes round number and syndicate size outliers, it is important to recheck whether these outliers affect the main results. Specifically, these outlier datapoints could just be natural outliers rather than mistakes or un-updated data. Hence, not including them can be vital to the validity of this analysis. After including these datapoints, table 11 show the round number and syndicate size characteristics for each type of VC syndicate after including outlier datapoints. Now, the maximum round number is 23 instead of 10 as seen in the main analysis. Similarly, for syndicate sizes, instead of having 12 as the maximum syndicate size, each type of VC syndicate has their individual maximum number. IVC syndicates have a maximum syndicate size of 40 VCs within a syndicate whereas FVCs and CVCs both have a maximum of 21 VCs within a syndicate.

Table 11 Round Number and Syndicate size characteristics for each type of VC syndicate after including outliers

Variable	Number of Observations	Mean	Minimum	Maximum
Round Number	12,267	2.249	1	23
IVC backed Syndicate Size	8853	3.355	1	40
FVC backed Syndicate Size	2252	2.492	1	21
CVC backed Syndicate Size	1077	4.604	1	21

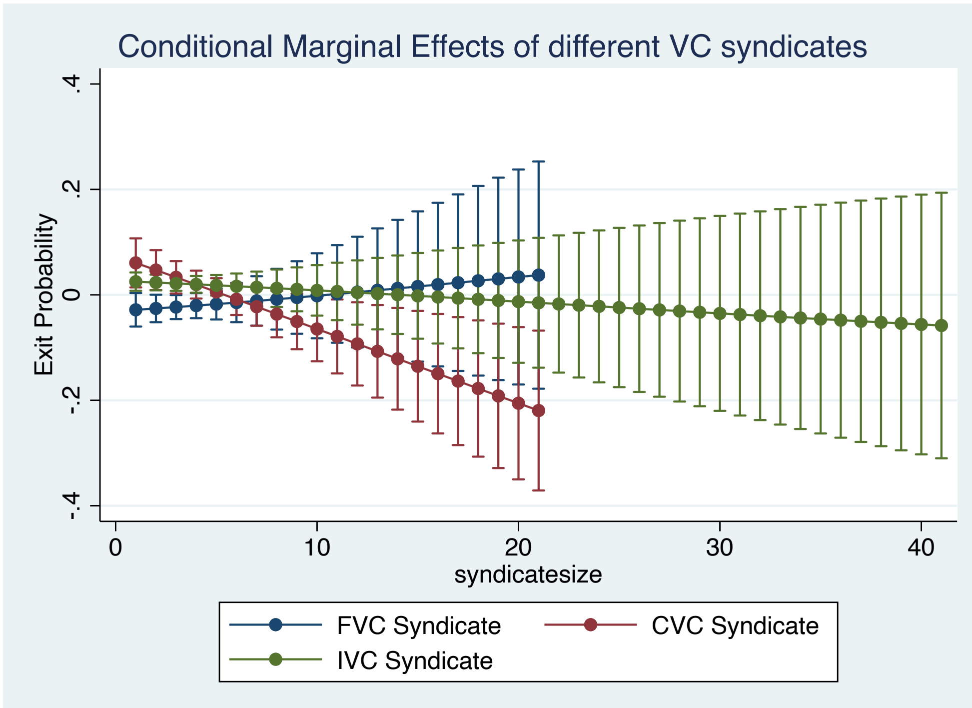
Regarding Hypothesis 1, the results are consistent with the main results (see Appendix, Table A19). Additionally, Hypothesis 2 also portray consistent results. However, the coefficients of the independent variables are much smaller relative to the main results. In particular, table 12 indicate that startups backed by IVC syndicates are more likely to exit by only 4 percentage points relative to startups with no syndication, ceteris paribus. This effect is statistically significant at the 1% significance level. This is much smaller relative to the 31.5 percentage point exit probability as shown in the main results. The same can be said for startups backed by CVC syndicates. Startups backed by CVC syndicates are more likely to exit by only 4,7 percentage points, ceteris paribus. This effect is statistically significant at the 1% significance level. With only a 0.7-percentage difference relative to the startups backed by IVC syndicates, this indicates that the difference in exit probability between CVC and IVC backed syndicates is also smaller in magnitude relative to the difference in the main results (5.9 percentage difference). Moreover, the results for hypothesis 3 are also consistent with the main results (see Appendix, Table A20). The only main difference is that for startups backed by CVC syndicates, larger syndicate sizes (syndicate sizes greater than 12) portray a more significant negative exit probability. However, figure 8 show that the confidence interval increases as the syndicate sizes increase. Therefore, results may not be accurate for greater syndicate sizes.

Table 12 Average Marginal Effects of Exit Probability of different VC syndicates after including outliers

Variable	Exit Probability
IVC_syn	0.040***
	(0.008)
FVC_syn	-0.006
	(0.013)
CVC_syn	0.047***
	(0.013)
rnumber	0.014***
	(0.002)
logtotalfunding	0.004*
	(0.002)
age	0.004***
	(0.001)
Investment Year dummies	YES
Sub-industry dummies	YES
Number of Observations	12,260
Log-probability	-4694.4215
R-squared value	0.310

Note. Robust standard errors in parantheses. The dependent variable is the exit status of the startup. The independent variable IVC_syn represents startups invested by IVC syndicates, FVC_syn represents startups invested by FVC syndicates and CVC_syn represents startups invested by CVC syndicates. The reference category is startups with no syndication. ***p-value < 0.01, **p-value < 0.05, *p-value < 0.

Figure 8 Scatterplot of Conditional Marginal Effects for different types of VC syndicates at various syndicate sizes on exit probability



6 Limitation and Future Research

It is important to note that this study is subject to limitations. Firstly, I could not control for the cultural difference FVCs may have with other VCs. Existing literature find that increases in cultural distance between VCs and startups reduces FVC investments (Cumming and Dai, 2010; Moore et al., 2015). Arguably, the best method to measure the cultural differences between VCs would be to use the measure adopted by Moore et al. (2015). They used four different dimensions to measure cultural distance developed by Hofstede (1980) namely: Power Distance Index, Individualism, Masculinity, and Uncertainty Avoidance Index. The data collected is survey-based and has been used by previous researchers. However, data on such unique indexes are challenging to find. Future research could rely on primary research, or various other databases that have information on cultural differences between countries.

Secondly, I was unable to explicitly control for the motivation of corporate investors (i.e., strategic vs. financial). Similarly, I was also unable to control for the startups' motivation to seek funding from CVCs. Being involved in a syndicate investment may not accurately reflect the motivation for startups seeking for or anticipating access to the incumbent's resources. According to Maula and Murray (2001), certain startups may seek CVC funding due to the VC's reputation. Others' top concerns center on access to R&D resources and expertise. Depending on the investment, various start-ups may have different reasons for engaging into a VC-startup relationship which could affect the exit probability of the startup (Nahata, 2008). I could not find any sources that provide VC and startup motivation for investing. Future research should look at news articles, primary data, or corporate announcements to investigate into this.

Thirdly, I could not control for other alternative explanations of exit performance. As previously mentioned, I measure exit performance indirectly by using exit status (whether the startup has exited or not via an M&A deal, IPO or an LBO). However, this type of variable ignores several aspects of exit performance, one of them being the timing of the exits. Exit timing information is important since it provides an understanding towards the startup's performance trajectory. Startups with rapid exits may be a sign of successful business concepts, robust market demand, or effective execution. Conversely, startups with slower exit times may have encountered difficulties or needed more time to grow. A solution to evaluate the performance trajectory of startups would be to perform a survival analysis and looking at the period from founding to exit. Dai and Kassicieh (2012) provides a good example by using the Cox Proportional Hazard model and uses the natural logarithm which is measured from the date of each round after being invested by an FVC. I attempted to use the survival analysis. However, I realized that the Refinitiv Eikon database does not provide the investment round dates for each investment. Future research should look at other data sources to gain dates of the investing round. This could be done by either looking at other databases or by conducting primary research with multiple venture capital funds.

Fourth, there may be several potential sources of bias from using a pooled cross-sectional data. By using a pooled cross-sectional dataset, the sample composition may change over time due to various unobserved firm-specific characteristics. For instance, it is possible that several startups are more likely to exit the market in specific years. If the exit patterns are not randomized and are connected to the exit probability of a startup, this may result in an unbalanced representation of different types of startups within the pooled dataset. I tried using year and sub-industry dummies to control for the unobserved time and sub-industry specific factors. A solution for this would be to use a panel dataset. Using a panel data enables the inclusion of startup-specific fixed effects controlling for the unobserved heterogeneity. Therefore, panel data can effectively control for the time-invariant factors and exploiting within-startup variations over time. Future research should consolidate with other databases or build a dataset through primary research that observes specific startups over time.

Fifth, one might argue that self-selection bias might occur due to several startups intentionally undisclosed several aspects of their business such as total funding amount. Some startups would want to remain private with the desire to maintain decision-making power and ownership (Boehmer and Ljungqvist, 2004; Brau and Fawcett, 2006). The founders' ambition to remain private frequently clashes with VCs' desire to go public because IPOs guarantee a timely return on their investment and have significant reputational advantages (Gompers and Lerner, 1996). Therefore, the non-disclosure of certain aspects of the startups can introduce bias into the sample because there could be systematic differences between startups that do disclose their funding and startups that do not. It is important to highlight that these are unobserved differences of the startups and hence it would be challenging to control for. A solution for this would be to conduct propensity score matching analysis. This way, we would be able to create comparable groups of startups that do disclose and do not disclose their total funding amount based on their observable differences.

Sixth, this analysis only considers computer software startups in the US. Hence, the sample is not randomly distributed. I selected the US as the country to analyze the effect of different types of venture capital due to the limited data availability in other countries (Maula, 2001; Maula et al., 2009). By only investigating the US, this reduces the external validity of the empirical results. It would be interesting to analyze the effects of VC investments and syndication towards exit probability at other countries. An example would be that future research should focus on analyzing the European market. Existing literature have characterized the European market with a lot of different cultures, diverse in terms of institutional attractiveness and big established companies having greater concerns for physical products (Groh et al., 2010; Rozenkopf et al., 2019). Additionally, it has been found that there are increasing regional integration from one European country to another (Moore et al., 2015). Hence, it would be interesting to investigate how the increases in cross-border regional integration as well as the big established European companies affects the exit probability of the European startups.

Seventh, I dropped startups that were invested by both CVC and FVC for simplicity reasons. This could introduce sample selection bias since these startups that are invested both by CVCs and FVCs may have unique characteristics different from those within this study. Future research should consider solutions such as including these startups in the analysis as a separate category, for example, co-invested startups.

Eighth, I did not control for the regulatory distance between foreign venture capital and the US-based startups. Specifically, regulatory differences may cofound the effect between foreign venture capital syndication and the probability to exit. Due to different regulatory restrictions, FVCs the US may have to operate differently relative to operating within their home country. Consequently, FVCs would have to cope with different organizational forms and their unique institutional requirements (Guo and Jiang, 2013). For example, strong legal systems, open financial markets, and efficient corporate governance systems define the regulatory forces in the Western countries. However, in developing countries such as China, these dynamics are not yet present. China has a very weak corporate governance, a weak legal system, opaque information, and limited reporting channels (Yang and Wang, 2018). Western nations emphasize the interests of investors and stakeholders, a viewpoint reinforced by their open systems and transparency norms. In contrast, the Chinese system prioritizes interpersonal ties (guanxi network) over the rights of shareholders or investors. These differences can affect the rate of syndication with FVCs in the US and subsequently, affecting the exit rates of startups invested by FVC syndications. Future research should use different measures to control for the regulatory distance between the FVCs and the investing country. A possible measure would be to use an external regulatory measure from the PRS International Country Risk Guide which is a time-variant metric representing the yearly dynamics of the host-country regulatory institutions. Higher scores correspond to the host nation's legal institutions, which range from 0 to 6 on the scale (Liu and Maula, 2021).

Ninth, I was not able to control for innovation performance. Existing literature have indicated that VC-backed companies are more likely to have a successful exit (Hellman and Puri, 2000; Darby and Zucker, 2002). Hellman and Puri (2000) find that innovative startups backed by VCs move more quickly to commercialize their innovations. Darby and Zucker (2002) emphasize that in the biotechnology industry, VCs foster innovation and enhances the probability to exit from the market. Future research should consider the innovation performance of the startup and use it as an additional control variable. One of the ways would be to use patents as a measure for innovation performance of each startup. This could be exported from external databases.

Tenth, I could not consider the relationship between the FVCs/CVCs and their partner investors. Specifically, Refinitiv Eikon does not reveal the position in which the FVCs and CVCs play within a particular investment round. Typically, in a investment round, an investor could act as the lead or a non-lead investor (Jaäskeläinen et al., 2006) whereby lead investors are more likely to have more communication duties with investees than non-lead investors (Wright and Lockett, 2003). Therefore, the contact between FVCs and CVCs and their investees may be influenced by their position within the investment round. As a result, I assume that all duties of FVCs/CVCs are not remarkably different from other types of investors.

Eleventh, it is important to acknowledge that this study suffers from endogeneity concerns. Specifically, this study is prone to sources of endogeneity such as omitted variable bias and reverse causality. For example, it is important to emphasize that unobserved heterogeneity, such as VCs having shared investment focus, is likely to be correlated with both syndication and exit probability. VCs that share similar investment focus may be more likely to syndicate on deals that are aligned with both of their shared focus and interests. At the same time, startups that are operating within those focus sectors may have a higher probability to exit due to the trend of the market or an increasing demand for startups within the respective focus. Moreover, I have highlighted several examples of variables that may potentially be omitted from this study within this limitations section. In terms of reverse causality, it is highly possible that, for example, VCs are well-informed initially about startups having greater exit probabilities with midsize syndicates relative to large syndicates. Hence, due to startups more likely to exit with midsize syndicates, they would invest in midsize syndicates portraying a reverse relationship. More specifically, the investment and syndication decisions could be affected by the exit performance of the startup. Future research should investigate these endogeneity concerns by using other methodologies such as utilizing an Instrumental Variable analysis, propensity score matching or conduct additional sensitivity analysis.

7 Conclusion

Overall, this study analyses the investment behavior of different forms of VC funds and at which stage of development are different forms of VCs more likely to invest. Additionally, I analyze how syndicated investments affect the exit probability of startups and how the exit probability varies for each syndicate size. Existing literature have demonstrated that startups invested by FVCs and CVCs are more likely to invest in later stages of development (Fulghieri and Sevilir, 2009; Dushnitsky and Shapira, 2010; Moore et al., 2015) and syndication with these VCs would positively affect the exit probability of startups (Dai et al., 2012; Bertoni et al, 2014) Cumming et al., 2016). However, it has not yet been tested whether the specifically FVC and CVC investments differ in exit probabilities for each syndicate size. By utilizing a pooled cross-sectional study of startups invested by IVCs, FVCs and CVCs operating in the United States between 2000 and 2023, I attempt to close this gap in the literature. The result within this analysis is valuable to both foreign/corporate investor and startups. For corporate and foreign investors, it is intriguing to see at which stage of development of the startup would bring the most value to them and at which level of syndication would yield best for the startups' exit probability. Whereas for startups, it can provide founders a measure to assess if a potential foreign or corporate investor is a suitable match for them.

The implications of this study are twofold. Firstly, foreign and corporate venture capitalists should be aware on the optimal syndicate size for their investments. Investing with too many VCs can result in larger coordination costs and therefore, decreasing the probability to exit for the startups. Based on this study, FVCs should look to invest with multiple IVCs whereas CVCs should invest in smaller syndicate sizes. Secondly, startup founders should carefully evaluate their own investment priorities. Specifically, startup founders should have a well-defined understanding of what they are seeking in an investment beyond just financial capital. While investing with greater syndicate sizes with FVCs or CVCs could secure funding for later stages and additional strategic benefits, this comes with a greater risk of conflict in objectives and coordination, vice versa. Hence, it is crucial for startups to strike a balance at which syndicate size level would be optimal for their startup profile. Above all, this present study concludes that, consistent with existing findings, FVCs and CVCs are more likely to invest in startups operating in the later or expansion stage relative to earlier stages. It also shows that being invested by a CVC syndicate would yield a greater startup exit likelihood relative to IVC syndicates for smaller syndicate sizes. However, investing with too many partners can lead to adverse effects such as coordination costs leading to lower startup exit probabilities. Additionally, due to the large confidence intervals and insignificant coefficients, these results must be interpreted carefully.

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9 Appendix

Table A1 Overview of Sub-Industries within the dataset

Sub-Industry Name	Frequency	Percentage
Agricultural Software	82	0.68
Applications Software	156	1.29
Artificial Intel. Programming Aids	6	0.05
Artificial Intelligence Related Softw..	116	0.96
Banks/Financial Institutions Software	775	6.41
Business and Office Software	2,133	17.63
Communications/Networking Software	171	1.41
Computer Software	1	0.01
Computer-Aided Instruction	32	0.26
Database & File Management	745	6.16
ERP/Inventory Software	473	3.91
Educational Software	268	2.22
Email Software	86	0.71
Expert Systems	872	7.21
Graphics and Digital Imaging Software	114	0.94
Groupware	129	1.07
Home Use Software	31	0.26
Integrated Software	66	0.55
Manufacturing/Industrial Software	130	1.07
Medical/Health Software	1,127	9.32
Multimedia software	274	2.26
Natural Language	150	1.24
Operating Systems & Utilities	86	0.71
Other Applications Software	539	4.46
Other Artificial Intelligence Related	293	2.42
Other Communications/Networking Softw..	256	2.12
Other Industry specific Software	457	3.78
Other Software Related	53	0.44
Other Systems Software	147	1.22
Program Development Tools/CASE/Langua..	193	1.60
Recreational/Game Software	550	4.55
Retailing Software	145	1.20
Scientific Software	49	0.41
Security/Firewalls, Encryption software	1,053	8.70

Systems Software	50	0.41
Transportation Software	290	2.40
Total	12,098	100.00

Table A2 Duplicates table by startup name throughout the 2000-2023 investment period

Number of Duplicates	Number of Observations	Surplus	Percentage
1	6815	0	53.455
2	4604	2302	36.113
3	1230	820	9.648
4	100	75	0.784

Table A3 Mann-Whitney-Wilcoxon (MWW) z-stat values of syndicate size by stage results

	Z-stat value Syndicate Sizes	
Stage	FVC-backed	CVC-backed
Seed	-19.954***	-21.197***
Early	-54.919***	-67.805***
Expansion	-45.770***	-58.502***
Later	-26.428***	-36.557***

***p-value < 0.01, **p-value < 0.05, *p-value < 0.1

Figure A1 Histogram of Total funding

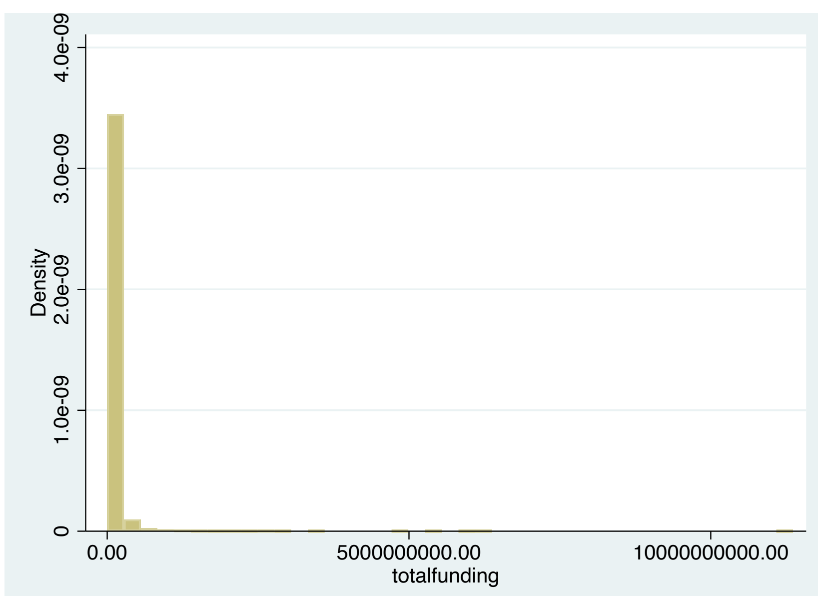

Table A4 Correlation Matrix

	stage	exit	CVC_backed	FVC_backed	IVC_backed	CVC_syn	FVC_syn	IVC_syn	rnumber	age	Logtotal funding	invyear	VEIC industry code	Syndicate size
stage	1.000													
exit	0.128***	1.000												
CVC_backed	0.030**	-0.016***	1.000											
FVC_backed	0.062***	-0.084***	-0.148***	1.000										
IVC_backed	-0.072***	0.083***	-0.506***	-0.779***	1.000									
CVC_syn	0.020**	-0.022**	0.9236	-0.137***	-0.467***	1.000								
FVC_syn	-0.008	-0.068***	-0.110***	0.745***	-0.580***	-0.102***	1.000							
IVC_syn	-0.031***	0.067***	-0.336***	-0.517***	0.664***	-0.310***	-0.385***	1.000						
rnumber	0.542	0.191	0.028	0.056***	-0.067***	0.016*	-0.035***	0.015	1.000					
age	0.456	0.499	-0.031	-0.075	0.085	-0.050***	-0.087***	0.005	0.354***	1.000				
logtotalfunding	0.277	0.107	0.060***	-0.043***	-0.001	0.065***	-0.030***	0.200***	0.388***	0.179***	1.000			
invyear	-0.093***	-0.534***	0.052***	0.121***	-0.139***	0.069***	0.095***	-0.048***	-0.154***	-0.872***	-0.091***	1.000		
VEICindustrycode	-0.022**	0.027**	0.007	0.006	-0.010	0.004	0.005	0.002	-0.007	0.002	0.022*	-0.012	1.000	
Syndicate size	0.015	-0.059***	0.153***	-0.174***	0.055***	0.208***	0.016*	0.421***	0.095***	-0.182***	0.238***	0.186***	0.012	1.000

Note. ***p-value < 0.001, **p-value < 0.05, *p-value < 0.1

Table A5 VIF Collinearity table

Variable	VIF	1/VIF
age	5.35	0.19
invyear	4.78	0.21
IVC_syn	1.50	0.67
FVC_syn	1.29	0.78
FVC_syn	1.29	0.78
CVC_syn	1.23	0.82
rnumber	1.46	0.69
FVC_invested	1.05	0.95
CVC_invested	1.03	0.97
VEICindustrycode	1.00	0.99
Logtotalfunding	1.28	0.78
Syndicatesize	4.25	0.24
logtotalfunding	1.28	0.78
Mean VIF	2.06	

Table A6 Round numbers tabulated before dropping 99th percentile outliers

rnumber	Frequency	Percentage	Cumulative Percentage
1	6,813	52.71	52.71
2	2,326	17.99	70.70
3	1,453	11.24	81.94
4	906	7.01	88.95
5	527	4.08	93.03
6	323	2.50	95.53
7	235	1.82	97.35
8	130	1.01	98.35
9	75	0.58	98.93
10	50	0.39	99.32
11	21	0.16	99.48
12	18	0.14	99.62
13	17	0.13	99.75
14	12	0.09	99.85
15	6	0.05	99.89
16	4	0.03	99.92
17	2	0.02	99.94

18	5	0.04	99.98
19	1	0.01	99.98
21	1	0.01	99.99
23	1	0.01	100.00
Total	12,926	100.00	

Table A7 Syndicate size tabulated before dropping 99th percentile outliers

syndicate size	Frequency	Percentage	Cumulative Percentage
1	3,334	27.18	27.18
2	2,39	19.48	46.66
3	1,877	15.30	61.96
4	1,463	11.93	73.89
5	1,142	9.31	83.20
6	759	6.19	89.39
7	473	3.86	93.24
8	301	2.45	95.70
9	189	1.54	97.24
10	122	0.99	98.23
11	81	0.66	98.89
12	52	0.42	99.32
13	23	0.19	99.50
14	18	0.15	99.65
15	12	0.10	99.75
16	10	0.08	99.83
17	5	0.04	99.87
18	1	0.01	99.88
19	2	0.02	99.89
20	4	0.03	99.93
21	2	0.02	99.94
23	2	0.02	99.96
24	2	0.02	99.98
25	1	0.01	99.98
29	1	0.01	99.99
40	1	0.01	100.00

Table A8 Average Marginal Effects of startup stage of development for Computer Software startups invested by FVCs and CVCs during the 2008-2009 financial crisis

Variable	Seed	Early	Expansion	Later
FVC_backed	-0.013	-0.007	0.007	0.013
	(0.025)	(0.014)	(0.014)	(0.024)
CVC_backed	-0.047	-0.025	0.027	0.046
	(0.029)	(0.017)	(0.017)	(0.028)
rnumber	-0.041***	-0.022***	0.023***	0.040***
	(0.007)	(0.006)	(0.003)	(0.006)
logtotalfunding	-0.005	-0.003	0.003	0.005
	(0.005)	(0.003)	(0.003)	(0.005)
age	-0.046***	-0.024***	0.026***	0.044***
	(0.006)	(0.006)	(0.003)	(0.002)
Investment year dummies	YES	YES	YES	YES
Sub-industry dummies	YES	YES	YES	YES
Log probability	-288.462	-288.462	-288.462	-288.462
R-squared value	0.470	0.470	0.470	0.470

Note. Standard errors in parantheses. The dependent variable is the stage of development of the startup. The independent variable FVC_backed represents startups invested by at least one FVC and CVC_backed represents startups invested by at least one CVC. The reference category is IVC_backed representing invested startups only invested by IVCs. The number of observations is 423 startups. The ordered logit regression in which the average marginal effects table was derived from has a log-probability value of -1288.461 and an R-squared value of 0.470. ***p-value < 0.01, **p-value < 0.05, *p-value < 0.1

Table A9 Average Marginal Effects of startup stage of development for Computer Software startups invested by FVCs and CVCs after the 2008-2009 financial crisis

Variable	Seed	Early	Expansion	Later
FVC_backed	-0.010***	-0.006***	0.012***	0.006***
	(0.003)	(0.002)	(0.003)	(0.002)
CVC_backed	-0.002	-0.001	0.002	0.001
	(0.004)	(0.002)	(0.004)	(0.002)
rnumber	-0.017***	-0.010***	0.018***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)
logtotalfunding	-0.003***	-0.002***	0.004***	0.002***
	(0.001)	(0.000)	(0.001)	(0.000)
age	-0.069***	-0.040***	0.070***	0.038***
	(0.002)	(0.002)	(0.001)	(0.000)

Investment year dummies	YES	YES	YES	YES
Sub-industry dummies	YES	YES	YES	YES
Log probability	-5183.273	-5183.273	-5183.273	-5183.273
R-squared value	0.568	0.568	0.568	0.568

Note. Standard errors in parantheses. The dependent variable is the stage of development of the startup. The independent variable FVC_backed represents startups invested by at least one FVC and CVC_backed represents startups invested by at least one CVC. The reference category is IVC_backed representing invested startups only invested by IVCs. The number of observations is 10,340 startups. The ordered logit regression in which the average marginal effects table was derived from has a log-probability value of -5183.273 and an R-squared value of 0.5684. ***p-value < 0.01, **p-value < 0.05, *p-value < 0.1

Table A10 Average Marginal Effects of Exit Probability for FVC and CVC syndicate investments for Computer Software Startups surrounding the 2008-2009 financial crisis

Variable	Pre-crisis	During Crisis	Post-Crisis
IVC_syn	0.060**	0.062	0.031***
	(0.025)	(0.054)	(0.008)
FVC_syn	0.033	-0.079	-0.002
	(0.060)	(0.095)	(0.013)
CVC_syn	0.109	0.201	0.034**
	(0.071)	(0.142)	(0.013)
rnumber	0.013	0.030*	0.017***
	(0.008)	(0.015)	(0.002)
logtotalfunding	0.037***	0.041**	-0.001
	(0.011)	(0.014)	(0.002)
age	0.009**	0.010	0.003**
	(0.005)	(0.007)	(0.001)
Investment Year dummies	YES	YES	YES
Sub-industry dummies	YES	YES	YES
Number of Observations	1331	423	10340
Log-probability	-727.081	-257.225	-3589.319
R-squared value	0.100	0.090	0.241

Note. Robust Standard errors in parentheses. The dependent variable is the exit status of the startup. The independent variable IVC_syn represents startups invested by IVC syndicates, FVC_syn represents startups invested by FVC syndicates and CVC_syn represents startups invested by CVC syndicates. The reference category is startups with no syndication. ***p-value < 0.01, **p-value < 0.05, *p-value < 0.1

Table A11 Conditional Marginal effects of exit probability for various syndicate sizes before the 2008-2009 financial crisis

Syndicate Size	FVC Syndicate	CVC Syndicate	IVC Syndicate
1	-0.008	0.090	0.004
	(0.108)	(0.121)	(0.039)
2	-0.014	0.068	0.003
	(0.073)	(0.091)	(0.031)
3	-0.019	0.048	0.002
	(0.061)	(0.069)	(0.038)
4	-0.023	0.030	0.001
	(0.076)	(0.061)	(0.050)
5	-0.027	0.013	-0.000
	(0.103)	(0.068)	(0.064)
6	-0.030	-0.003	-0.001
	(0.131)	(0.086)	(0.076)
7	-0.033	-0.018	-0.002
	(0.157)	(0.109)	(0.086)
8	-0.034	-0.030	-0.002
	(0.181)	(0.132)	(0.093)
9	-0.036	-0.042	-0.003
	(0.200)	(0.155)	(0.099)
10	-0.037	-0.052	-0.003
	(0.216)	(0.177)	(0.102)
11	-0.037	-0.061	-0.003
	(0.228)	(0.199)	(0.104)
12	-0.037	-0.068	-0.003
	(0.237)	(0.219)	(0.104)

Note. Standard errors in parentheses. The dependent variable is the exit status of the startup. The independent variable IVC_syn represents startups invested by IVC syndicates, FVC_syn represents startups invested by FVC syndicates and CVC_syn represents startups invested by CVC syndicates. The reference category is startups with no syndication. ***p-value < 0.01, **p-value < 0.05, *p-value < 0.1

Figure A2 Scatterplot of Conditional Marginal Effects at different syndicate sizes on exit probability before the 2008-2009 financial crisis

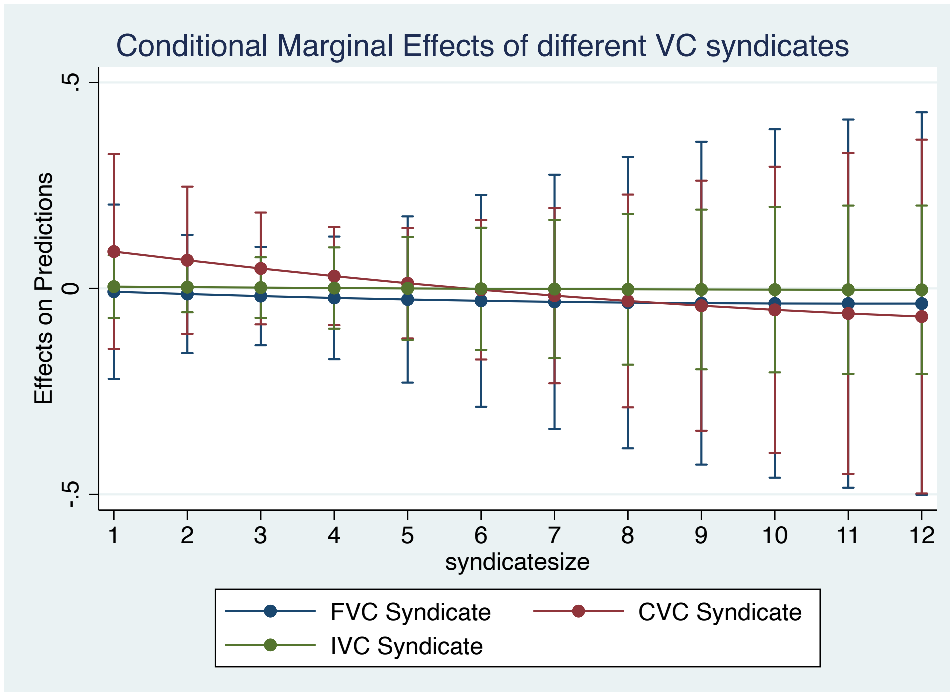

Table A12 Conditional Marginal effects of exit probability for various syndicate sizes during the 2008-2009 financial crisis

Syndicate Size	FVC Syndicate	CVC Syndicate	IVC Syndicate
1	-0.128	0.090	0.030
	(0.128)	(0.121)	(0.074)
2	-0.135	0.068	0.038
	(0.101)	(0.091)	(0.058)
3	-0.141	0.048	0.046
	(0.092)	(0.069)	(0.065)
4	-0.147	0.030	0.053
	(0.106)	(0.061)	(0.088)
5	-0.152	0.013	0.061
	(0.137)	(0.068)	(0.118)
6	-0.155	-0.003	0.068
	(0.176)	(0.086)	(0.149)
7	-0.158	-0.018	0.074
	(0.217)	(0.109)	(0.180)
8	-0.160	-0.030	0.080

	(0.258)	(0.132)	(0.210)
9	-0.161	-0.042	0.086
	(0.298)	(0.155)	(0.239)
10	-0.161	-0.052	0.091
	(0.336)	(0.177)	(0.266)
11	-0.160	-0.061	0.095
	(0.371)	(0.199)	(0.291)
12	-0.158	-0.068	0.099
	(0.403)	(0.219)	(0.314)

Figure A3 Scatterplot of Conditional Marginal Effects at different syndicate sizes on exit probability during the 2008-2009 financial crisis

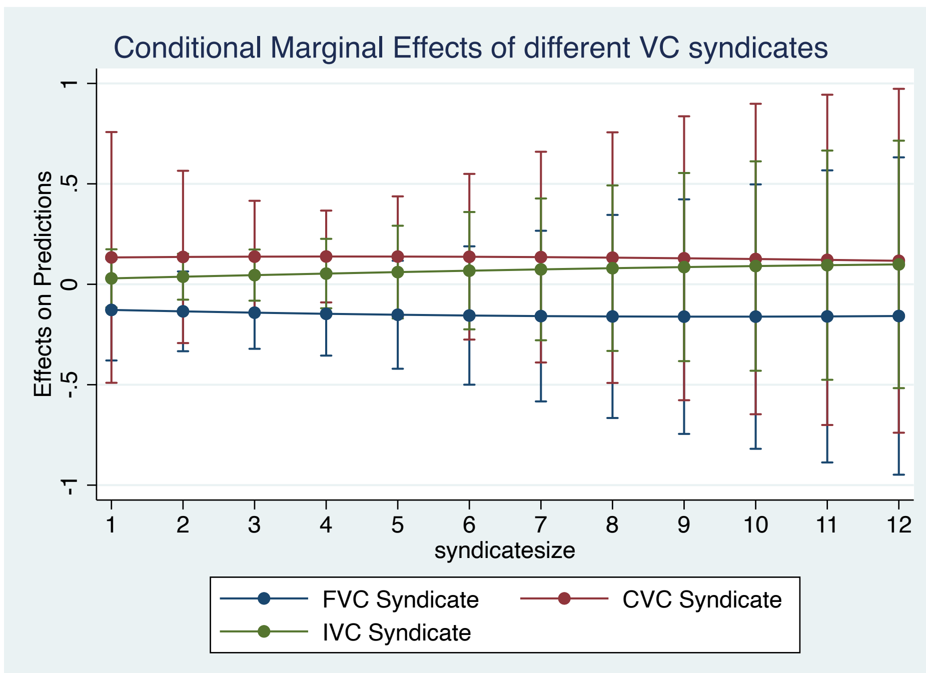

Table A13 Conditional Marginal effects of exit probability for various syndicate sizes after the 2008-2009 financial crisis

Syndicate Size	FVC Syndicate	CVC Syndicate	IVC Syndicate
1	-0.026	0.043*	0.023**
	(0.016)	(0.025)	(0.010)
2	-0.025*	0.033**	0.022**
	(0.013)	(0.020)	(0.008)
3	-0.023**	0.024**	0.020**
	(0.011)	(0.016)	(0.007)
4	-0.022*	0.014	0.018**
	(0.012)	(0.014)	(0.008)
5	-0.020	0.004	0.017
	(0.016)	(0.013)	(0.010)
6	-0.018	-0.006	0.015
	(0.021)	(0.015)	(0.013)
7	-0.016	-0.016	0.013
	(0.028)	(0.018)	(0.016)
8	-0.014	-0.026	0.011
	(0.034)	(0.022)	(0.019)
9	-0.012	-0.035	0.009
	(0.042)	(0.027)	(0.023)
10	-0.010	-0.045	0.007
	(0.049)	(0.031)	(0.026)
11	-0.008	-0.055	0.005
	(0.0573)	(0.036)	(0.030)
12	-0.005	-0.066	0.003
	(0.066)	(0.040)	(0.034)

Figure A4 Scatterplot of Conditional Marginal Effects at different syndicate sizes on exit probability after the 2008-2009 financial crisis

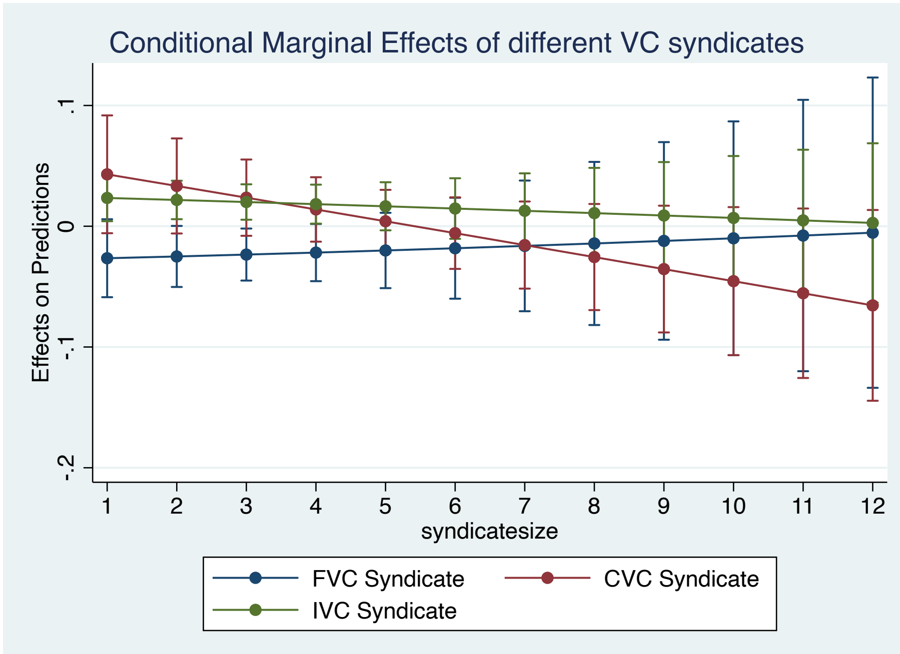

Table A14 Conditional Marginal effects of M&A probability for various syndicate sizes

Syndicate Size	FVC Syndicate	CVC Syndicate	IVC Syndicate
1	-0.022	0.071**	0.041***
	(0.018)	(0.026)	(0.010)
2	-0.021	0.055**	0.036***
	(0.014)	(0.021)	(0.008)
3	-0.020*	0.039**	0.030***
	(0.012)	(0.016)	(0.007)
4	-0.019	0.023*	0.023***
	(0.013)	(0.014)	(0.009)
5	-0.018	0.007	0.017
	(0.017)	(0.014)	(0.011)
6	-0.017	-0.009	0.011
	(0.023)	(0.017)	(0.014)
7	-0.016	-0.026	0.004
	(0.029)	(0.021)	(0.017)
8	-0.015	-0.042*	-0.003
	(0.036)	(0.025)	(0.021)

9	-0.014	-0.058*	-0.010
	(0.044)	(0.030)	(0.024)
10	-0.013	-0.075**	-0.017
	(0.051)	(0.035)	(0.028)
11	-0.011	-0.091**	-0.024
	(0.059)	(0.040)	(0.032)
12	-0.010	-0.108**	-0.031
	(0.067)	(0.045)	(0.036)

Note. Robust standard errors in parentheses. The dependent variable is the exit status of the startup. The independent variable IVC_syn represents startups invested by IVC syndicates, FVC_syn represents startups invested by FVC syndicates and CVC_syn represents startups invested by CVC syndicates. The reference category is startups with no syndication. ***p-value < 0.01, **p-value < 0.05, *p-value < 0.1

Figure A5 Scatterplot of Conditional Marginal Effects at different syndicate sizes on M&A probability

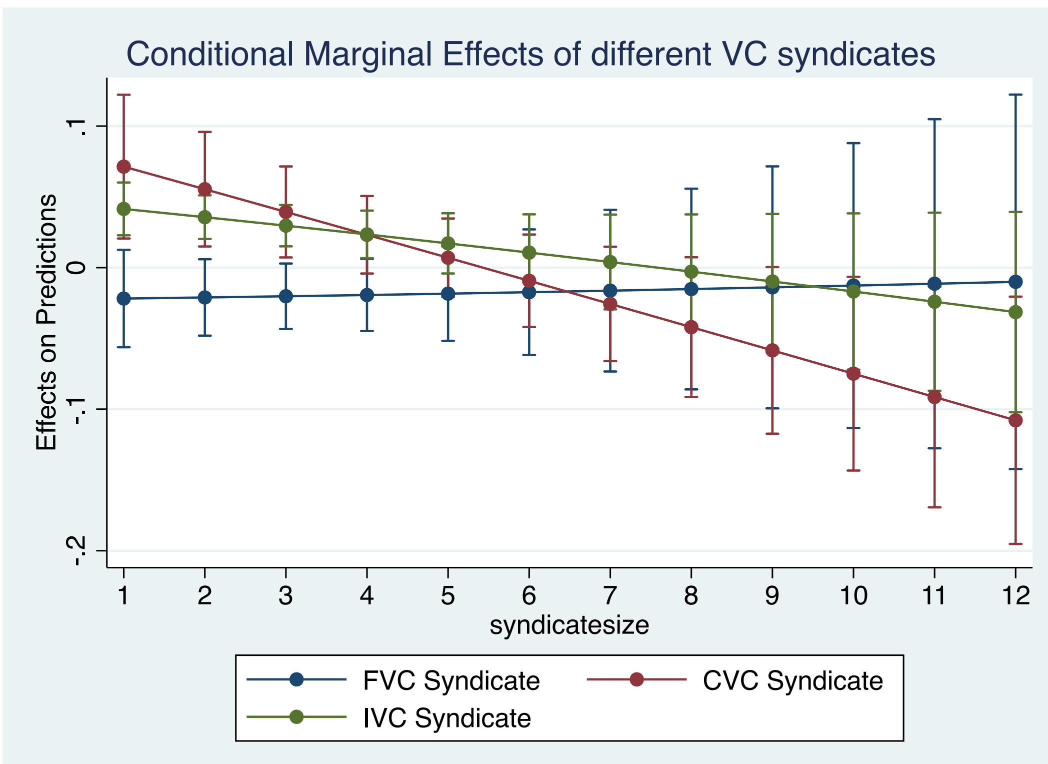

Table A15 Conditional Marginal effects of IPO probability for various syndicate sizes

Syndicate Size	FVC Syndicate	CVC Syndicate	IVC Syndicate
1	-0.009	-0.010	-0.005
	(0.009)	(0.008)	(0.005)
2	-0.009	-0.010	-0.003
	(0.007)	(0.007)	(0.004)
3	-0.010*	-0.009	-0.000
	(0.005)	(0.006)	(0.004)
4	-0.010*	-0.008	0.002
	(0.005)	(0.005)	(0.004)
5	-0.010	-0.007	0.005
	(0.006)	(0.005)	(0.005)
6	-0.011	-0.006	0.007
	(0.009)	(0.006)	(0.006)
7	-0.011	-0.004	0.009
	(0.011)	(0.007)	(0.007)
8	-0.012	-0.003	0.012
	(0.014)	(0.009)	(0.008)
9	-0.012	-0.001	0.014
	(0.016)	(0.012)	(0.009)
10	-0.012	0.002	0.017
	(0.019)	(0.015)	(0.010)
11	-0.013	0.002	0.019*
	(0.022)	(0.018)	(0.012)
12	-0.013	0.004	0.022*
	(0.025)	(0.021)	(0.013)

Note. Robust standard errors in parentheses. The dependent variable is the exit status of the startup. The independent variable IVC_syn represents startups invested by IVC syndicates, FVC_syn represents startups invested by FVC syndicates and CVC_syn represents startups invested by CVC syndicates. The reference category is startups with no syndication. ***p-value < 0.01, **p-value < 0.05, *p-value < 0.1

Figure A6 Scatterplot of Conditional Marginal Effects at different syndicate sizes on IPO probability

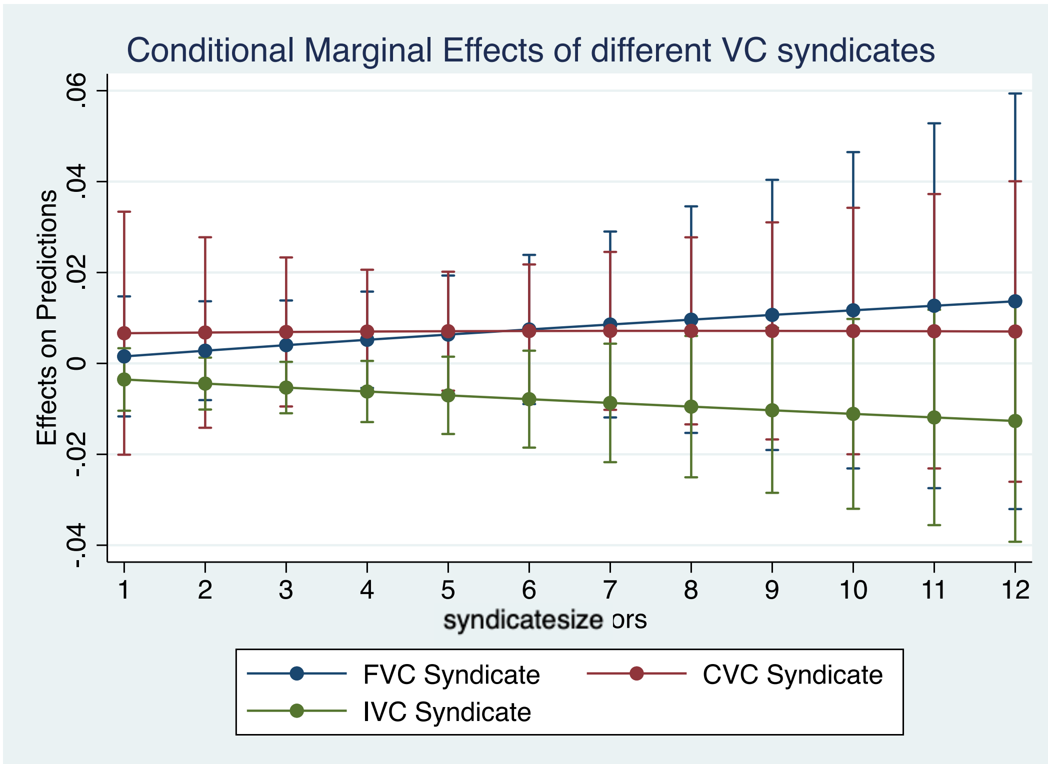

Table A16 Conditional Marginal effects of LBO probability for various syndicate sizes

Syndicate Size	FVC Syndicate	CVC Syndicate	IVC Syndicate
1	0.002	0.007	-0.004
	(0.007)	(0.014)	(0.004)
2	0.003	0.007	-0.004
	(0.006)	(0.011)	(0.003)
3	0.004*	0.007	-0.005
	(0.005)	(0.008)	(0.003)
4	0.005*	0.007	-0.006
	(0.005)	(0.006)	(0.003)
5	0.006	0.007	-0.007
	(0.007)	(0.007)	(0.004)
6	0.007	0.007	-0.008
	(0.008)	(0.007)	(0.005)
7	0.009	0.007	-0.009

	(0.010)	(0.009)	(0.007)
8	0.010	0.007	-0.010
	(0.013)	(0.010)	(0.008)
9	0.011	0.007	-0.010
	(0.015)	(0.012)	(0.009)
10	0.012	0.007	-0.011
	(0.018)	(0.014)	(0.011)
11	0.013	0.007	-0.012
	(0.020)	(0.015)	(0.012)
12	0.014	0.007	-0.013
	(0.023)	(0.017)	(0.014)

Note. Robust standard errors in parentheses. The dependent variable is the exit status of the startup. The independent variable IVC_syn represents startups invested by IVC syndicates, FVC_syn represents startups invested by FVC syndicates and CVC_syn represents startups invested by CVC syndicates. The reference category is startups with no syndication. ***p-value < 0.01, **p-value < 0.05, *p-value < 0.1

Figure A7 Scatterplot of Conditional Marginal Effects at different syndicate sizes on LBO probability

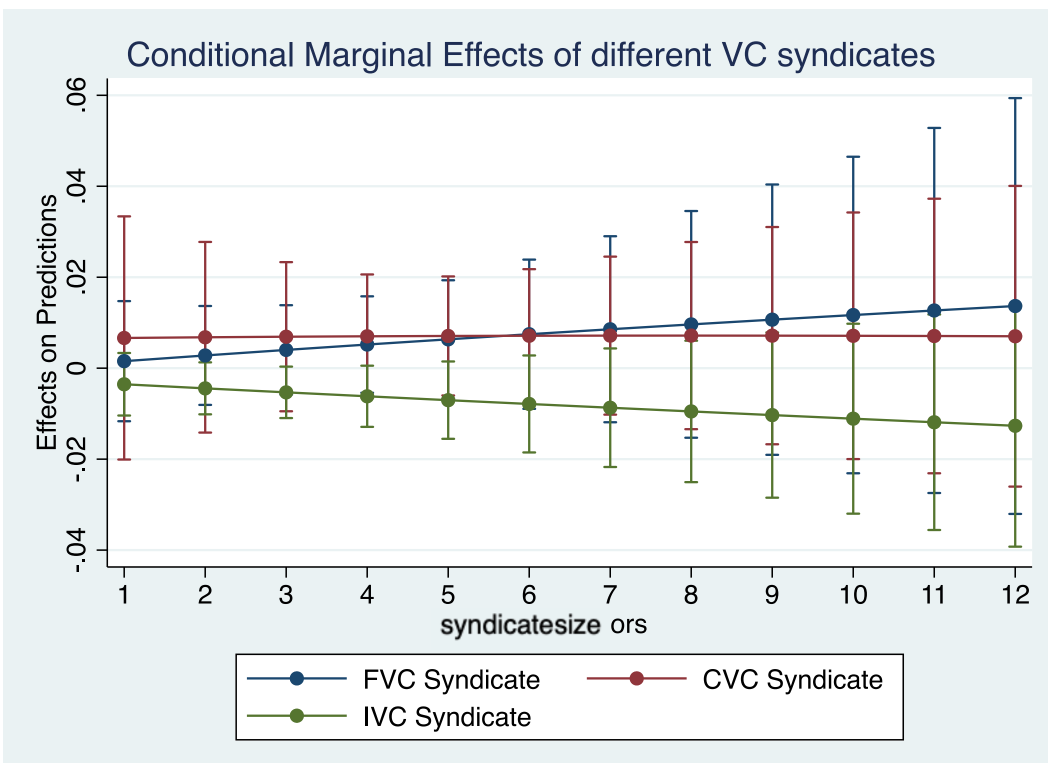

Table A17 Average Marginal Effects of startups stage of development for midsize syndicate startups invested by FVCs and CVCs

Variable	Seed	Early	Expansion	Later
FVC_backed	-0.006*	-0.005*	0.006*	0.004*
	(0.003)	(0.002)	(0.003)	(0.002)
CVC_backed	-0.002	-0.001	0.002	0.001
	(0.004)	(0.003)	(0.005)	(0.003)
rnumber	-0.022**	-0.018**	0.024**	0.016**
	(0.001)	(0.001)	(0.001)	(0.001)
logtotalfunding	-0.005**	-0.004**	0.005**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
age	-0.055**	-0.045**	0.061**	0.039**
	(0.002)	(0.001)	(0.001)	(0.001)
Investment year dummies	YES	YES	YES	YES
Sub-industry dummies	YES	YES	YES	YES
Log-probability	-6339.360	-6339.360	-6339.360	-6339.360
R-squared value	0.473	0.473	0.473	0.473

Note. Robust standard errors in parantheses. The dependent variable is the exit status of the startup. The independent variable IVC_syn represents startups invested by IVC syndicates, FVC_syn represents startups invested by FVC syndicates and CVC_syn represents startups invested by CVC syndicates. The reference category is startups with no syndication. ***p-value < 0.01, **p-value < 0.05, *p-value < 0.1

Table A18 Average Marginal Effects of Exit Probability for midsize FVC and CVC syndicate investments for the investment period 2000-2023

Variable	Exit Probability
IVC_syn	0.305***
	(0.062)
FVC_syn	-0.025
	(0.109)
CVC_syn	0.397***
	(0.124)
rnumber	0.138***
	(0.018)
logtotalfunding	0.038**
	(0.019)
age	0.030***
	(0.009)
Investment Year dummies	YES
Sub-industry dummies	YES

Number of Observations	10,122
Log-probability	-4052.064
R-squared value	0.297

Note. Robust standard errors in parantheses. The dependent variable is the exit status of the startup. The independent variable IVC_syn represents startups invested by IVC syndicates, FVC_syn represents startups invested by FVC syndicates and CVC_syn represents startups invested by CVC syndicates. The reference category is startups with no syndication. ***p-value < 0.01, **p-value < 0.05, *p-value < 0.

Table A19 Average Marginal Effects of startups stage of development after including outliers

Variable	Seed	Early	Expansion	Later
FVC_backed	-0.006**	-0.005**	0.006**	0.004**
	(0.003)	(0.002)	(0.003)	(0.002)
CVC_backed	0.000	0.000	-0.000	-0.000
	(0.003)	(0.003)	(0.004)	(0.002)
rnumber	-0.021***	-0.017***	0.023***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)
logtotalfunding	-0.005***	-0.004***	0.005***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
age	-0.055***	-0.045***	0.061***	0.039***
	(0.002)	(0.001)	(0.001)	(0.001)
Investment year dummies	YES	YES	YES	YES
Sub-industry dummies	YES	YES	YES	YES
Log-probability	-4036.221	-4036.221	-4036.221	-4036.221
R-squared value	0.374	0.374	0.374	0.374

Note. Robust standard errors in parantheses. The dependent variable is the exit status of the startup. The independent variable IVC_syn represents startups invested by IVC syndicates, FVC_syn represents startups invested by FVC syndicates and CVC_syn represents startups invested by CVC syndicates. The reference category is startups with no syndication. ***p-value < 0.01, **p-value < 0.05, *p-value < 0.1

Table A20 Conditional Marginal Effects of startups stage of development after including outliers

Syndicate Size	FVC Syndicate	CVC Syndicate	IVC Syndicate
1	-0.028*	0.061**	0.025***
	(0.016)	(0.024)	(0.009)
2	-0.026*	0.047**	0.023***
	(0.013)	(0.019)	(0.008)
3	-0.023**	0.033**	0.022***
	(0.012)	(0.016)	(0.007)

4	-0.020*	0.019	0.020**
	(0.012)	(0.013)	(0.008)
5	-0.018	0.006	0.018*
	(0.015)	(0.013)	(0.010)
6	-0.015	-0.008	0.016
	(0.019)	(0.015)	(0.012)
7	-0.011	-0.022	0.014
	(0.024)	(0.018)	(0.015)
8	-0.008	-0.036	0.012
	(0.029)	(0.022)	(0.018)
9	-0.005	-0.051*	0.011
	(0.035)	(0.027)	(0.021)
10	-0.002	-0.065**	0.009
	(0.041)	(0.031)	(0.024)
11	0.002	-0.079**	0.006
	(0.047)	(0.036)	(0.028)
12	0.005	-0.093**	0.004
	(0.054)	(0.040)	(0.031)
13	0.009	-0.107**	0.002
	(0.060)	(0.045)	(0.035)
14	0.012	-0.121**	0.000
	(0.066)	(0.049)	(0.038)
15	0.016	-0.135**	-0.002
	(0.073)	(0.054)	(0.041)
16	0.019	-0.150**	-0.004
	(0.079)	(0.058)	(0.045)
17	0.023	-0.164***	-0.006
	(0.085)	(0.062)	(0.049)
18	0.027	-0.178***	-0.008
	(0.092)	(0.066)	(0.052)
19	0.030	-0.192***	-0.011
	(0.098)	(0.070)	(0.056)
20	0.034	-0.206***	-0.013
	(0.104)	(0.074)	(0.059)
21	0.037	-0.219***	-0.015
	(0.110)	(0.077)	(0.063)
22			-0.017
			(0.066)
23			-0.020
			(0.070)

24	-0.022
	(0.074)
25	-0.024
	(0.077)
26	-0.026
	(0.081)
27	-0.029
	(0.084)
28	-0.031
	(0.088)
29	-0.033
	(0.091)
30	-0.035
	(0.094)
31	-0.037
	(0.098)
32	-0.040
	(0.101)
33	-0.042
	(0.104)
34	-0.044
	(0.107)
35	-0.046
	(0.111)
36	-0.048
	(0.114)
37	-0.050
	(0.117)
38	-0.052
	(0.120)
39	-0.054
	(0.123)
40	-0.056
	(0.126)

Note. Robust standard errors in parantheses. The dependent variable is the exit status of the startup. The independent variable IVC_syn represents startups invested by IVC syndicates, FVC_syn represents startups invested by FVC syndicates and CVC_syn represents startups invested by CVC syndicates. The reference category is startups with no syndication. ***p-value < 0.01, **p-value < 0.05, *p-value < 0.1