CORPORATE VENTURE CAPITAL AND STARTUP SURVIVAL

AN ABSTRACT

SUBMITTED ON THE TWENTIETH DAY OF MAY 2023

TO THE AB.FREEMAN SCHOOL OF BUSINESS

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

OF THE GRADUATE SCHOOL

OF TULANE UNIVERSITY

FOR THE DEGREE

OF

DOCTOR OF PHILOSOPHY

BY

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Abstract

This paper examines the causal effect of corporate venture capital (CVC) investors on the survival of startups. Using parent firm merger and acquisition events as a shock to geographical exposure to venture arms thereof, I find that exposure to CVCs increases the likelihood of having a next round and having a successful exit subsequently. The hazard rate of a next round and that of a successful exit are, respectively, 3% and 7% higher with the CVC exposure than without it. Exposure to CVCs attracts better-networked VC investors. Exposure to better-networked CVCs only increases the likelihood of a next round but not that of a successful exit after the current round.

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1 Introduction

There is an increasing number of non-financial firms investing in innovative startups. The investments are usually made through a corporate venture capital (hereon, CVC) division or a CVC subsidiary. One famous example is GV (formerly known as Google Ventures), the CVC arm of Google. In 2021, more than 1,800 unique CVCs invested in at least one deal. The number of deals with CVC participation grew by 50%, and the total deal value with CVCs doubled compared to 2020.[1]

There are two reasons why CVCs are special and worth studying. First, CVCs are different from conventional venture capital firms (hereon, VCs). For CVCs, their motivation of investments are more strategic rather than financial (Gompers and Lerner 2000; Shan 2018; Ma 2019). For startups, the resources they can receive from CVCs complement those from VCs. (Maula, Autio, and Murray 2005). Second, a selection issue exists in CVC investments. Literature shows that CVC-backed startups tend to have better ultimate exits (Gompers and Lerner 2000; Gompers et al. 2002; Ivanov and Xie 2010; Chemmanur and Chen 2014). However, not all startups prefer CVCs to VCs. Some people think of CVCs as "pet projects"[2] and some other fear that the CVC-backed startups can be faced with the "negative signaling" risk if the CVCs withdraw their investment in the future (McCahery and Vermeulen 2016). Given these distinct features of CVCs, does their participation in an investment round have a casual impact on the survival of startups?

To answer the above question, I explore the transaction round-level data from Refinitiv (formerly known as Thomson One VentureXpert) and do a survival analysis using the competing hazard model. This model enables one to study different survival results at the same time, while taking into consideration the different time spans between adjacent rounds. In addition, the survival analysis design mitigates the data censoring problem (Cleves, Gould, Gould, Gutierrez, and Marchenko 2008). For startups that are missing

[1] PitchBook, NVCA and Insperity: Venture Monitor of 2021Q4

[2] BCG, How the Best Corporate Ventures Keep Getting Better, August 2018.

exit/survival information, I do not need to make any assumptions to keep them in the sample.

To solve the identification issue caused by the two-sided matching between CVCs and startups, I introduce a plausibly exogenous proxy for CVC exposure. The rationale for this proxy is that startup companies in a location are more likely to be funded by a CVC if the parent firm of that CVC merges with or acquires a firm in the same location. In other words, the expansion in geographical footprint of CVC parents can increase the CVC exposure of local startups. The underlying assumption is that the merger decisions of the parent are not driven by CVC deal-making preferences. Instead, the M&A activity of the CVC parent serves as a shock to the personal network of the local entrepreneur, introducing them to the CVC fund managers and making them potential targets of CVC investments. Through a set of validation tests, I show that parent M&As robustly predicts significantly higher CVC subsidiaries/divisions activities in locations where the M&A targets are located, while tightly controlling for location and pair fixed effects. The effect is still robust when I change the level of parent M&As (CVC transactions) to increase in parent M&As (increase in CVC transactions) and when I use different measurement windows.

In order to apply this shock to round-level data, for each venture capital transaction (each round for each startup), I calculate the increase in the number of CVC parents that make M&As in the startup location and use it as my exogenous proxy for CVC investment. Using this exogenous shock, a causal link between CVC exposure and the survival of startups is established. Analyses show that exposure to CVCs will increase the likelihood of having a next round and having a successful exit subsequent to the current round. The effect is robust after controlling for the presence of VCs, the startup stage (the presence of buyout investors), transaction year, startup industry, and merger waves at the location level. Finally, I explore the possible mechanisms behind the effect. Using a dynamic network measure, I show that startups exposed to CVCs are attracting better-networked VC investors. Moreover, exposures to different types of CVCs have different impacts on startup survival.

Another important takeaway is that the results using the exogenous shock are different from the results using potentially endogenous variables (i.e., the actual CVC presence dummy). This indicates that there indeed exists a selection bias and that the exogenous research design is necessary. This finding is consistent with previous literature (Sørensen 2007; Ewens, Gorbenko, and Korteweg 2019) that shows a two-sided matching in the venture capital investment decision-making and contracting process. Venture capitalists are picking promising startups, while startups are also picking investors for their own interests.

This paper has several contributions. First of all, this paper establishes a causal link between CVCs and startups. Existing literature looks into the outcomes of the cross-section of startups if they are once backed by CVCs (Gompers and Lerner 2000; Gompers et al. 2002; Ivanov and Xie 2010; Chemmanur and Chen 2014; Chemmanur, Loutskina, and Tian 2014). For example, Ivanov and Xie (2010) find that startups backed by CVCs are more likely to have a successful exit eventually. The endogeneity issue, however, is not being fully addressed in this line of literature. There still lacks a good shock to exogenize CVC presence.[3] So the impact of CVCs on startups remains unclear. This paper proposes an exogenous proxy for CVC exposure and identifies a causal impact of CVCs on the survival of startup companies. In addition, this exogenous shock can be applied to other CVC-related research in the future.

Second, this paper studies the impact of CVCs on the interim survival of startups instead of on the ultimate exit outcomes. The exiting literature of CVCs focuses on the startup-level results and see if the presence of CVCs can influence the ultimate exits of startup companies. However, the success rate of startup company is only around 10%. The effect of CVC on the other 90% are unclear, and the process by which CVCs are related to the ultimate exit is not explored enough. For example, for those startups that are ultimately written-off, CVCs may help them survive longer or get the next round of investment faster. Using more nuanced round level data, this paper provides a new angle to look at the role CVCs play by exploring the information contained in venture capital transactions.

Third, to my knowledge, this is the first paper to use the competing hazard model to analyze the impact of CVCs on round-level startup survival. The hazard model can fully exploit the information contained in the time gaps between adjacent rounds. More importantly, with the cause-specific competing hazard model, the effect of CVCs on mu-

[3] Chemmanur, Loutskina, and Tian (2014) use propensity score matching (PSM) to get a sample of VC-backed startups as the control for CVC-backed startups. Given the limitation of PSM, the endogeneity problems may still exist.

tually exclusive outcomes can be separated and observed at the same time. An additional benefit of using the hazard model is that censored observations can be kept with weaker assumptions.

The rest of the paper is organized as follows: Section 2 summarizes related literature. Section 3 reports the sample selection procedures and summary statistics. Section 4 elaborates on the details in the research design and methodology. Section 5 presents testing results. Section 6 concludes the paper.

2 Related Literature

2.1 Corporate Venture Capital

Most of the existing literature looks at the bright side of CVCs. Researchers document that CVC-backed companies are more likely to go public, have a higher IPO valuation or takeover price (Gompers and Lerner 2000; Gompers et al. 2002; Ivanov and Xie 2010) and once they are public, they are more innovative than other VC-backed companies due to the failure-tolerance feature of CVCs (Chemmanur, Loutskina, and Tian 2014). The parent firm, a firm that has a CVC arm, on the other side, can also achieve an increase in its own innovation output and firm valuation (Dushnitsky and Lenox 2005; Dushnitsky and Lenox 2006). They attribute the mutual value-adding to cooperative relationships between the CVC parent firm and the startup. However, a recent working paper of Tian and Ye (2020) finds that CVC arms also have a dark side in that they will induce an overinvestment problem in the parent firms, which can ultimately decrease their shareholder value. Ma (2019) is one of the first papers that investigate the strategic purpose of CVCs empirically. The paper looks into the motivations when industrial firms start and stop making CVC investments and the innovation outcomes of that process. The paper shows that industrial firms make CVC investments when they are experiencing a deterioration of their internal innovations, and they terminate CVC arms when their internal innovations recover. These results are consistent with industrial firms using CVC investments as a strategic fix for their innovation weakness.

2.2 Venture Capital Networks

Many papers have been looking at networks in the traditional venture capital market. Hochberg, Ljungqvist, and Lu (2007) study the relationship between VC networks and investment performance. They show that at both the fund level and the portfolio startup company level, VCs that possess more influential positions (more centralized) in the networks have better investment performance. Hochberg, Ljungqvist, and Lu (2010) find that incumbent VCs in local markets form barriers to restrict the entry of outside VCs so that they can pay lower prices for their investments. The VCs do so by threatening the incumbents who cooperate with the new entrants with the withdrawal of future network access. For example, they stop co-investing with the "betrayer" in future investments. The denser the network is, the harder it is for the new entrants to enter the local market. The results in these two papers are consistent with reciprocity behaviors among VCs documented in earlier literature (Lerner 1994). In other words, they all show that VCs will exchange their access to different markets. Furthermore, Hochberg, Lindsey, and Westerfield (2015) develops a generalized method and test the existence of similarity-based matching, cumulative advantage, and resource sharing in the VC co-investment network. They show that VCs exchange value-add resources other than capital (e.g., access, experience, investment scope) for capital.

However, there are also findings about the non-cooperation among familiar VCs. Du and Hellmann (2019) find that VCs in less central positions or VCs that are making investments in more active markets tend to get "tired" of their past co-investors. Deeper past relationship leads to fewer future co-investment and worse performance in future co-investments. This line of literature shows how the presences of venture capital investors can influence the performance of each other as well as the performance of startups, which calls for the necessity to control the presence of VCs when studying the impact of CVCs.

Another line of literature studies the dynamics of contracting between VCs and their portfolio startups. Sørensen (2007) builds a structural model to show that there is a two-sided matching in VC investments, where experienced VCs tend to invest in better startup companies. Ewens, Gorbenko, and Korteweg (2019) find that VCs use their bargaining power to benefit more from the contract terms instead of maximizing startup outcomes. These studies show that the matching between startups and VCs is dynamic and endogenous, which could also be true for CVCs, making the introduction of an exogenous shock even more necessary.

2.3 M&A as Exogenous Shock

Mergers and acquisitions are regarded as plausibly exogenous shocks for certain firm behaviors and are used as a shock in many studies. For example, Derrien and Kecskés (2013) use the merger of brokers as an exogenous shock to analyst coverage. Kim and Singal (1993) examine the price changes affected by the increase in market share using airline mergers as a natural experiment. Another branch of literature studies the impact of bank mergers on corporations (Bonaccorsi di Patti and Gobbi 2001; Degryse, Masschelein, and Mitchell 2011). Hence, mergers and acquisitions can be viewed as an exogenous shock and used as an instrument for the endogenous independent variable as long as the dependent variable is not driven by the M&A directly.

3 Data

3.1 Venture Capital Transaction Data

Data for this paper is collected from Refinitiv (formerly known as Thomson One VenturєXpert). I download all the related data with transaction years between 1962 and 2021. The data includes startup company information (company name, company industry, company address, etc.), firm investor information (investor name, investor type, investor founding date, etc.), transaction information (transaction date, transaction round, deal value, etc.), and startup exit information (exit date, exit type, etc.). I classify investors that are labeled as "Corporate PE/Venture" and make "Generalist Private Equity" investments as CVCs. I classify investors that are labeled as "Private Equity Firm", "Bank Affiliated", "Insurance Firm Affiliate", or "Investment Management Firm" and make "Generalist Private Equity" investments as VCs.[4] Investors who make "Buyout" investments are classified as buyout investors. Relative to VC investors, buyout investors usually invest in more mature businesses and are much bigger in size (Axelson, Strömberg, and Weisbach 2009). I therefore control for the presence of buyout investors to control for a startup's stage. In the competing hazard model, controlling for buyout investors also helps tease out their impact on the likelihood of a leveraged buyout (LBO) exit. The remaining investors are classified as other investors, including angel groups, incubators, pension funds, FOF, government-affiliated ventures (GVCs), and small business investment companies (SBICs), which I do not distinguish among. There are 22,196 investors in my final sample. Of these investors, 2,598 are CVCs and 15,007 are VCs. According to Refinitiv, 18,582 of them are still actively making investment as of the end of 2021. Detailed treatment for duplicate investors and startup companies are in Appendix A.

[4]Investors recorded as "Bank Affiliated" or "Insurance Firm Affiliate" in VentureXpert corresponds to the so called "financial service CVC". I classify these investors as independent VCs (conventional VCs) in this paper. Their investment incentives are mostly financial, which aligns more with the investment incentive of VCs. However, the results remain unchanged if I classify them as CVCs.

Table 1 presents the startup level summary statistics. As stated in Panel A, there are 111,021 startups in the final sample. They have 2.02 rounds on average. Most of them are backed by VCs, which means at least one of the rounds has VC investors. Only 21,007 of them are backed by CVCs, of which most are backed by only one CVC. The industries of the startups are defined based on VEIC (venture economics industry classification), which is an industry classification method used by VentureXpert and SDC Platinum for both public and private firms. There are four levels of VEIC classifications: VEIC3 (industry), VEIC2 (sub-sector), VEIC1 (sector), and VEIC Class (class). I use VEIC2 in all my empirical analyses. It includes 68 sub-sectors. Panel B presents the VEIC1 sector distribution of startups. 24.67% of the startups are computer software companies, and 20.75% are internet companies. On average, 18.92% of the startups are backed by CVCs. However, this percentage varies by sector. In biotechnology sector the percentage is as large as about 28.22%. In semiconductor/electronic sector, communications sector, computer hardware and software sectors, and internet sector, more than 22% of the startups are backed by CVCs. Yet in sectors like construction, the portion of startups backed by CVCs can be as low as around 6%.

Panel C summarizes the exit types of the startups.[5] Following Tian and Ye (2020), for those startups that are missing exit information, if they receive their last investment before Dec 31, 2018 (three years before the end of my data window), I mark them as "inactive". In other words, if a startup with missing exit information fails to receive any new investments for three years, it is regarded as being written-off. All the remaining startups are marked as "censored", which means they are still under active management as of the end of my data window. If a startup exits by going public, M&A or LBO, it is a successful exit. 18,892 startups are in this category. If a startup is written off by its investors or becomes inactive for more than three years, it is a failed exit. 65,666 startups end up with failed exits.[6]

[Insert Table 1 around here.]

[5] To avoid duplication, only the first exit of each startup is kept. For example, if a startup is acquired and then brought public later on, I only keep the M&A exit and all the investments it received before the M&A exit. Less than 3% of the startup companies have more than one exits.

[6] The remaining 26,463 startups with censored exits are only included in round-level analyses. They are not in the sample of the replication test in Table A1.

Table 2 summarizes round-level data. In this table and in the later round-level analyses, every observation represents one transaction round of one startup. For example, if a startup experiences three rounds of investment before it exits, there will be three observations for this startup in the round-level data. All the LBO and M&A rounds that serve as exits are dropped. The final sample consists of 236,186 rounds in total, of which 34,969 rounds have CVC investors. Panel A summarizes the data for the full sample. Panel B (C) summarizes the data for rounds with (without) CVC investors. For the rounds with CVCs present, most of them have only one CVC. On average, the rounds with CVCs happen at the startup company age of 1.5 years and in the second round. Compared with rounds without CVCs, rounds with CVCs happen at later years (higher *log(Company age)*) and later rounds (higher *Round number*). In addition, in these rounds with CVCs present, startup companies receive more investment (higher *log(Deal value)*).

[Insert Table 2 around here.]

3.2 Geographical Footprint Data

I match US CVCs in my sample to their parent firms using names and addresses. First, I utilize the link table used in Ma (2019), and link the CVCs to their public parent firms. Next, I perform a name match with 100% similarity score to link the remaining CVCs to their parent using information in CapitalIQ. Finally, for the rest of the unmatched CVCs, most of which are CVC divisions rather than CVC subsidiaries, I manually match them to their parent firms using their information in Capital IQ. I successfully match 388 CVCs to their parent firms with identifiable gvkeys.

To get the M&A footprint of the parents, I search for all the M&A deals where the CVCs parents act as the acquirer (target) in Thomson Reuters SDC Platinum and record the ZIP codes of the target (acquiring) firm. M&A ZIP codes from SDC Platinum and company ZIP codes from Refinitiv are then translated into CBSAs[7] using the link table provided by Stanford Center for Population Health Science.[8] Only US ZIP codes can be linked to

[7]CBSA stands for "Core Based Statistical Area". It is the metropolitan and metropolitan statistical area delineation defined by the United States Office of Management and Budget (OMB). It is more granular than state and less granular than city.

[8]Stanford Center for Population Health Science https://redivis.com/StanfordPHS

CBSAs, so M&A deals and startup companies located outside of the US are dropped. There are 939 CBSAs in the US, of which 392 are MSAs (metropolitan statistical areas) and 547 are μSAs (micropolitan statistical areas). Figure 1 presents the heat-map of venture capital activities by CBSA and Table 3 lists the top 30 CBSAs ranked by numbers of venture capital transactions. San Francisco-Oakland-Hayward ranks the highest with 19,304 transactions during the sample years.[9]

[Insert Table 3 around here.]

[9] Sample years are 1980 to 2020. Noted that the link table between gvkey and cusip are not updated for the year 2021, therefore, M&As and venture capital deals for 2021 are dropped. Most M&A data before 1980 are missing location and industry information, which is the reason why M&As before 1980 are also dropped.

4 Methodology

4.1 Survival Analysis Using Competing Hazard Model

Survival analysis is a method to study the impact of a treatment on "time to event" of outcomes. It is widely used in biomedical sciences to study the effect of treatment on time to an event (e.g., death or recovery of patients or of laboratory animals). Another use is in modeling the time it takes for machines or electronic components to break down. Nowadays it is also used by social scientists to study job promotion, marriage, faculty retention, etc. The developments from these diverse fields have been consolidated into the methodology of "survival analysis" (Allison 1984). In finance, there has not been many studies that implement survival analysis. One if the few examples is Barber and Yasuda (2017), which uses survival analysis to study the impact of interim fund performance of private equity funds on their ability to fundraise.

The key concept of survival analysis is the hazard rate. It is the rate at which a certain event can occur at time t. The definition function of hazard rate is:

$$h(t) = \lim_{dt \to 0} \frac{Pr(t \leq T < t + dt)}{dt \times S(t)} = \frac{f(t)}{S(t)} = -\frac{S'(t)}{S(t)} \tag{1}$$

Where $S(t)$ is the survival function defined as:

$$S(t) = Pr(T > t) \tag{2}$$

A standard method to estimate the hazard function at time t is the Cox proportional hazard model:

$$h(t|X_i) = h_0(t) \times exp(\boldsymbol{X_i'\beta}) \tag{3}$$

It assumes the hazard rate for each subject at time t to be proportional to a base rate

$(h_0(t))$. The multiplier is the exponential of some function of its characteristics ($\boldsymbol{X_i'}$). The βs that we get from the Cox regression is the marginal effect of each covariate on the occurrence of the event. One unit of change in the covariate increases the probability of the event from $h_0(t)$ to $h_0(t) \times exp(\boldsymbol{X_i'\beta})$. In other word, at time t, the probability of the event with one more unit of the covariate is $exp(\boldsymbol{X_i'\beta})$ times the probability without it.

This Cox proportional hazard model is also what Barber and Yasuda (2017) use in their study. They model the hazard rate for raising a follow-on fund by the fund manager as a function of fund characteristics. In this paper, I model the hazard rate of round outcomes, as a function of investor and round characteristics. However, in contrast to Barber and Yasuda (2017), where the only event is failing to receive any new funding (which translates to two outcomes, "failed to receive new funding" and "receive new funding"), in my case, there are three competing outcomes for any transaction round, which are getting a next round, successful exit, and failed exit. So I need to separately estimate the probability for each outcome. Therefore, I apply the cause-specific hazard function to each possible outcome c:

$$h_c(t) = \lim_{dt \to 0} \frac{Pr(t \leq T < t + dt)}{dt \times S(t)} = \frac{f_c(t)}{S_c(t)} = -\frac{S_c'(t)}{S_c(t)} \tag{4}$$

Meanwhile, the basic form of the Cox proportional hazard model is replaced by a cause-specific hazard model, which allows the coefficient before each covariate to differ by event type (outcome c). What is more, I allow the base rate at t ($h_0(t)$) to vary by outcome type, transaction year and startup industry by implementing a stratum of type/year/ind (stratum s). The stratum works like a fixed-effect in the exponent part ($\boldsymbol{X_i'\beta}$) that eventually changes the base rate $h_0(t)$ into $h_{0s}(t)$. The stratified case-specific hazard model is as follow:

$$h_s(t|X_i) = h_{0s}(t) \times exp(\boldsymbol{X_i'\beta_c}) \tag{5}$$

In this way, I can separately estimate the base rate for each competing outcomes in each year and industry. Detailed explanation with an example is given in the next section.

4.2 CVC Investments Explained by Geographical Footprint of Its Parent

To study the causal relationship between CVC presence and startup survival, I proxy for the propensity to receive CVC investment using the net increase in CVC exposure. To be more specific, for each startup round, if we denote the transaction month (month of the round investment date) as month zero, I calculate the change in the number CVC parent doing M&A in month [-12,0) from the number of CVC parent doing M&A in month [-24, -12) with targets/acquirers in the startup CBSA. I assume that if the number is positive, then the startup is more likely to receive investment from CVCs in the round. In other words, if there are more CVC parent firms merging with firms in a certain location compared to last year, it is more likely for CVCs to be present in venture capital transaction in that location.

To validate this proxy for CVC exposure, I regress CVC investment on parent M&A activity. 388 pairs of CVC-parent are collected as discussed in the data section. For every CVC-parent pair x, CBSA y and year z, I calculate the number of US domestic M&As made by the parent firm in CBSA y during the year z-1 ($\textit{Number of Parent M\&As}_{xyz}$), the change in M&A made by the parent firm in CBSA y in year z-1 compared to year z-2 ($\textit{Change in Number of Parent M\&As}_{xyz}$), the number of venture capital deals the CVC participates in CBSA y in year z ($\textit{Number of CVC Deals}_{xyz}$), and the change in number of venture capital deals the CVC participates in CBSA y in year z compared to year z-1 ($\textit{Change in Number of CVC Deals}_{xyz}$). Then, I create four dummies based on the four measures, which equal one if the corresponding measure is positive (*Parent Makes M&As*, *Parent Makes More M&As*, *CVC Makes Deals*, and *CVC Makes More Deals*). I expect to see that the number of parent M&A activity can be a strong predictor of the number of CVC venture capital deals.

The results are presented in Panel A of Table 4. Every observation is one combination of CVC-parent pair x, CBSA y and year z. Many CBSAs are not investment-active at all, and therefore, there will be a lot of zeros in the regression data. In columns (1) and (3), CBSAs that have less than 100 venture capital deals in the sample years are dropped. I am left with 75 CBSAs that are investment-active. In columns (3) and (4), I keep all the CBSAs. The results remain the same. Dependent variable in columns (1) and (2) is *CVC Makes*

Deals, a dummy that equals one if the CVC in pair x make venture capital investment in CBSA y in year z, and equals zero otherwise. Independent variable is *Parent Makes M&As*, a dummy that equals one if parent in pair x do M&A in CBSA y in year z-1, and equals zero otherwise.

This result shows that M&As made previously by parents are associated with CVC deals in the same location. In columns (3) and (4), I change the independent variable and the independent variable to dummies that mark the changes in the numbers. The results show that, even if we take last year into consideration and only look at the net increase, parent M&A is still strongly associates with CVC venture capital transactions. I change the window for parent M&A from past 12 months to past 36 months (from past one year to past three years) and repeat the tests. As shown in Panel B, the results stay the same. All the regressions are controlled for pair, year, CBSA fixed effects, and clustered at CBSA level.

[Insert Table 4 around here.]

Finally, this table proves that when a parent firm merges or acquires firms in one CBSA, it is more likely for its CVC arm to do venture capital transactions in the same location afterwards. To incorporate this relationship into my round-level data setting, for each observation i (each round for each startup) in my sample, I create a variable that measures the net increase in number of CVC parents doing M&A investments in time window t and CBSA s. t is the 12 months before transaction date. s is the CBSA of the startup company. Then the dummy *More CVC Exposure* is created that equals one if this net increase is positive and zero otherwise. This dummy will be the exogenous proxy for CVC's presence in the transaction i. As for the exogeniety of this shock, it is very unlikely that a parent firm merges with another firm in a certain location because it wants its CVC branch to invest in the same location. To further address this concern, I repeat the tests in the follow-on analyses with a proxy constructed in a slightly different way: excluding M&A deals investing in the same VEIC2 sub-sector as the startup. In other words, the results are robust if I restrict the M&A shock to be the ones aimed at local firms that operate outside of the startup industry. Hence, the increase in the number of CVC parents in one location is my exogenous proxy for local startups' propensity to receive CVC investments in the current round.

Note that all the CVC-parent pairs in this paper are restricted to the ones with public parents. There are several reasons not to include private parents. First, private parents don't have an universal identifier to link to M&A database, and their public information is also limited, making it even less reliable to do a name/address match. Second, M&As made by private parent firms are usually also private deals. Missing M&A ZIP code will result in those M&A deals being dropped anyway. The assumption is that exposure to CVCs with a public parent firm is effective enough to proxy for propensity to receive CVC investments.

5 Results

5.1 Startup Company Level

To make sure that my sample is representative and consistent with prior studies, I replicate the startup level results that examine the correlation between CVCs and successful exits (Gompers and Lerner 2000; Gompers et al. 2002; Ivanov and Xie 2010; Chemmanur and Chen 2014). I define the dependent variable *Successful Exit* as one if the startup company ultimately has a successful exit (IPO, Merger, or LBO). Otherwise, unless it is censored[10], *Successful Exit* is defined to be zero. *Backed by CVCs (BOs)* is one if at least one CVC (buyout) investor invested in the startup before it exits. Startups with more rounds are more mature and have received more fundings by the time of exit, and thus are more likely to have successful exits. Therefore, *Total number of rounds*, defined as the total number of rounds a startup has received before its exit, is controlled. *Company Age* is defined as number of years between the date when the startup receive its first investment and its exit date.[11] *Funding Received* is the total funding received by the startup company by the time it exits in millions USD. I take the log of *Funding Received* and *Company Age* to account for the skewness in their distributions.

Results are presented in Appendix Table A1. From the univariate test in Table A1, Panel A, we can see that being backed by a CVC is associated with a higher probability of having a successful exit. The result holds in the multivariate test in Panel B. When *Successful Exit* is regressed on *Backed by CVCs*, and other control variables, the coefficient is significantly positive even with industry and exit year fixed effect and industry cluster. Hence my sample is similar to that in extant literature.

[Insert Table A1 around here.]

[10] If the last investment round of a startup company happens within three years before the data coverage ends, it is hard to tell if the startup company is being inactive/written-off or not. Startups of this kind are dropped from the startup company-level regression.

[11] Many startups are missing founding date data. So I use the first investment date instead of the founding date.

5.2 Round Level OLS

Startup level analysis does not take into consideration the time when CVCs get involved. By looking directly at the ultimate exits, one may ignore the process by which CVCs are effecting the survival of the company. That is why round-level analyses are meaningful. The dependent variable *Survive* is defined as one if the startup has a next round or exits successfully subsequent to current round. In contrast, if the startup has a failed exit after this round or becomes inactive ever since, *Survive* is zero. *CVCs Present (VCs Present/Buyout investors Present)* is defined as one if there exits at least one CVC (VC/buyout) investor in the round and is defined as zero otherwise. *Deal Value* is the total dollar value of this transaction round measured in millions USD. *Company Age* is the number of years since the startup receives its first investment. Any missing first investment date is supplemented with the first observed transaction date of the startup company. I take the log of *Deal Value* and *Company Age* to address the skewness in their distributions. The round level regression is as follow, for any startup company i and round n:

$$Survive_{in} = \alpha_i + \beta_1 \times CVCs\,Present_{in} + \beta_2 \times VCs\,Present_{in} + \beta_3 \times BOs\,Present_{in} + Controls_{in} + \epsilon_{in} \quad (6)$$

β_1 will tell us the correlation between CVC presence and round-level survival of startup company. The results are reported in Table 5. The univariate test in Panel A shows that conditional on not having any VC investor, the startup is 2.7% more likely to survive the current round with the presence of CVCs. Conditional on having VC investors, the startup is 5.88% more likely to survive the current round with the presence of CVCs. The OLS regression in Panel B, shows that the presence of CVCs is correlated with a higher likelihood of surviving the current round. The presences of VCs and buyout investors are also positively correlated with startup survival. However, bundling several different survival outcomes into one dependent variable can be problematic. The presence of CVCs may increase the likelihood of one type of survival while decrease that of the other type, making the overall effect less informative.

[Insert Table 5 around here.]

5.3 Round Level Survival Analysis using Competing Hazard Model

When two mutually-exclusive outcomes, "having next round" and "successful exit", are bundled together into the one variable *Survive*, it is making the result less comprehensible. Moreover, the information about the time span between adjacent rounds are not being fully utilized. Therefore, I use the aforementioned competing hazard model to repeat the round-level survival analysis. A round received one for the dummy *Next Round* if the company receives another round of investment afterwards. The round receives one for the dummy *Successful Exit* (*Failed Exit*) if it exit after this round and falls into the corresponding successful exit (failed exit) category in Panel C of Table 1. As discussed in section 4.1, the stratified cause-specific hazard model works as follow:

$$h_s(t|X_{in}) = h_{0s}(t) \times exp(\boldsymbol{X'_{in}\beta_c}) \tag{7}$$

Where X_{in} is a vector of characteristics of round n for startup i, which can be *CVCs Present*, *VCs Present*, *Buyout Investors Present*, or some other controls. The coefficient before each characteristic (β_c) in the parameter vector will tell us the marginal effect of that covariate on the outcome c. t is the time between this round and the next round. If there is an exit after this round, t is set to be the time between this round and exit date. If the startup becomes inactive after this round, t is set to be three years. If the startup exit type is censored, following **?**, I assume the exit date to be the end of 2021. Fixed effect will bias the competing hazard model (Cox model) drastically (Allison 2002). To make up for the missing of fixed effects, I include strata into the models to allow different base ratios for different stratum. All the models are stratified by startup industry/transaction year/outcome.

For example, if we are looking at the probability of having a next round (define it as outcome 1) for firm i in round n with stratum s the model will be[12]:

$$
\begin{aligned}
h_s(t|X_{in}) &= h_{0,s}(t) \times exp(\boldsymbol{X'_{in}\beta_1}) \\
&= h_{0,s}(t) \times exp(\beta 1, 1 \times CVC\,Presence_{in} + \beta 2, 1 \times VC\,Presence_{in} \\
&+ \beta 3, 1 \times BO\,Presence_{in})
\end{aligned} \tag{8}
$$

Table 6 shows the result of survival analysis with the marginal effect of each variable and the corresponding t-stat in bracket. Like discussed in section 4.1, the probability of the event with one more unit of the covariate is e^{β} times the original probability. Take the first specification (Model 1) as an example, the presence of CVC is associated with a decrease in the likelihood of having a next round and a failed exit, and is associated with an increase in the likelihood of having a successful exit. To interpret results, for a given industry and transaction year, the hazard for having a next round with CVCs is about 0.946 ($e^{-0.056}$) of that without CVCs. The hazard of having a successful exit with CVCs, however, is about 1.172 ($e^{0.159}$) of that without CVCs. The results tell that *CVCs present* is positively associated with having a successful exit subsequently but negatively associated with having a next round and a failed exit.

[Insert Table 6 around here.]

5.4 Competing Hazard Model with Exogenous Shock

There could exist some selection bias in the previous survival analysis. Specifically, the matching between startups and investors is dynamic. The dummy variable *CVC Present* can suffer from an endogeneity problem. Therefore, it is crucial to explore an exogenous shock to CVC and see if the effect of CVC still exits. Here, I use the M&A footprint of CVC parents in a certain location as the proxy for CVC exposure for all the startups in that location. The relevance of this proxy is proved in the methodology section.[13]

[12] Note that strata in this paper are at industry/year/outcome level, so strata will always nest outcome types. Here, it means all the observation in stratum s has outcome of 1. But not all outcome 1 observations are in stratum s.

[13] To double check the validation of this shock, I regress number of all investors, number of VC investors and number of CVC investors on this exogenous measure and present the results in Appendix Table A2. The exogenous measure increase the number of CVCs in the current round, while has no significant effect on the number of all investors and VC investors.

For each observation (startup i, round n), I define a variable *More CVC Exposure*. It is recorded as one if the number of CVC parent firms doing M&A in startup CBSA increases in the past 12 months, and is recorded as zero otherwise. I replace *CVCs Present* in the competing hazard model with *More CVC Exposure* and run the same stratified competing hazard model. *More M&A Activities* is a dummy variable that equals one if the number of all M&As (not only the ones made by CVC parents) increases in the CBSA. It controls for the increase in baseline M&A activities. The results are presented in Table 7. All three specifications show that the increase in CVC exposure causes an increase in the probability of having a next round and the probability of having a successful exit, and has no significant impact on the probability of failed exit. I still stratify the models by startup industry/transaction year/outcome. Standard errors are clustered at the industry level.

It is worth noting that results in the competing hazard model with the exogenous shock are different from those in Table 6 with the endogenous *CVCs Present* dummy. With the exogenous shock, we can draw a conclusion that CVC exposure has a positive impact on the probability of having a next round and having successful exit subsequently. For any given industry and transaction year, the hazard of having a next round with CVC exposure is 1.024 ($e^{0.024}$) times of that without CVC exposure. The hazard of having a successful exit subsequently with CVC exposure is 1.073 ($e^{0.070}$) times of that without CVC exposure.

The table shows that CVC exposure effects are significant even after controlling for the presence of VCs and buyout investors. The analysis here shows no effect of CVCs on the probability of having a failed exit and an opposite effect on having a next round of fundings compared to Table 6. This suggests that there do exist some omitted variables or selection biases in the endogenous research design. The significant correlation between *CVCs Present* and probability of having a failed exit in those endogenous regressions can be spurious. It may also be the reason why the effect of *CVCs Present* on the probability of having a next round is falsely negative in the endogenous regressions. However, the insignificance of CVC exposure on failed exit could also be a result of limited sample size, so I cannot fully reject the alternative hypothesis that the exposure to CVCs has effect on the probability of having a failed exit.

[Insert Table 7 around here.]

5.5 Robustness Tests

It is possible that the CVC parents do M&As in certain CBSA because they are looking for opportunities in a specific industry that is dominant in that CBSA. As a results, startups in the same industry will be more likely to survive by becoming the M&A targets of these parents in the future. The increase in the probability of survival caused by the overall M&A activities, therefore, may have nothing to do with the CVC arms. To address this concern, I construct the exogenous measure in a slightly different way by excluding M&As in the same industry as that of the startup. The new measure *More CVC Exposure* equals one if the number of CVC parents doing M&As outside of the startup industry in the CBSA increases in the past 12 months. The new control *More M&A Activities* equals one if the number of all the M&As outside of the startup industry in the CBSA increases in the past 12 months. I repeat the tests and present the results in Table 8. The results are robust and even more significant. Specifically, the hazard of having a next round with CVC exposure is 1.029 ($e^{0.029}$) times of that without CVC exposure. The hazard of having a successful exit subsequently with CVC exposure is 1.073 ($e^{0.070}$) times of that without CVC exposure.

[Insert Table 8 around here.]

Still, M&A waves of different industries can coincide with each other. So I want test and see if the increase in startup survival (especially the increase in successful exit) only attributes to increase in M&A exit. I further separate the exit types and create five different outcome categories (*Next Round, M&A Exit, LBO Exit, IPO Exit and Failed Exit*) and repeat the previous tests. Results are in Table 9. The positive impact of CVC exposure on successful exit is not only explained by the increase in the hazard of M&A exit, but also by increase in the hazard of LBO exit. So the impact of CVC exposure on successful exit is not driven by local M&A wave.

[Insert Table 9 around here.]

Another way to address the concern that the M&A activities are endogenous is to look at the industry distribution (measured by VEIC sector) of treated startups and the M&A target firms. In Figure 2, I plot the industry of the treated startup and the that of M&A target that triggers the increase in M&A exposure into a heat-map. Computer Software and Internet Specific sectors appear to be the hottest venture capital investments in the sample. It also appear that startups in these two sectors are more likely to be exposed to CVCs whose parents were also interested in these two sectors. This could be a location effect that is already addressed by the location-specific fixed effect in Table 7. But as a robustness test, I drop startups in these two sectors and repeat the main test. Results are tabulated in Table A6. The significant effect of having a next round still exists, while the effect of having a successful exit is not significant anymore. However, given that the size of this sub-sample is only half of that of the full sample, I cannot reject the hypothesis that the exogenous shock has no effect on having a successful exit.

Furthermore, I test the industry migration of CVC's investments before and after the M&A of its parent firm in Figure 3 to see if there is any dispersion across the industries in which they invest. Panel A shows the CVC investments before and after an M&A. x-axis is the VEIC sectors of last CVC investment before the M&A. y-axis is the VEIC sectors of the first CVC investment after the M&A. To further decompose the migration. Panel B and Panel C compare the industry distributions of last CVC investments before M&A, M&A targets, and first CVC investments after M&A. There is no identifiable patterns on the diagonals except for Computer Software and Internet Specific sectors. Therefore, there is not any identifiable relationships between parents' M&A investments and CVC's investments in the industry dimension.

5.6 Possible Mechanisms

The venture capital industry is an intertwined network where capitalists with relationships exchange their resources. The reputation and style of one investor will affect other investors' willingness to join the co-investment (Hochberg, Ljungqvist, and Lu 2010; Hochberg, Lindsey, and Westerfield 2015; McCahery and Vermeulen 2016). It is found that more centralized VCs are associated with more successful startups (Hochberg, Ljungqvist, and Lu 2007). Therefore, if exposure to CVCs can attract other investors that are more centralized, then CVCs may influence the survival of startup companies through this channel.

Following Hochberg, Ljungqvist, and Lu (2007) and Hochberg, Lindsey, and Westerfield (2015), I construct a network of co-investor ties for each monthly-rolling, five-year window, and calculate the eigenvector centrality[14] of every investor in each network. In Panel A of Table A5, I regress the average and maximum eigenvector centrality of investors in the current round on *More CVC Exposure* dummy. For both, the overall investors and new investors (who have never invested in the startups before), their average centrality and maximum centrality are higher with more exposure to CVCs. In Panel B, I further control for the corresponding eigenvector centrality of last round. This will drop the first observed rounds of any startup company, resulting in a smaller sample. The eigenvector centrality of current round investors is still positively correlated with CVC exposure.

The results imply that startup companies who are exposed to CVCs have more centralized investors in later rounds. According to Hochberg, Ljungqvist, and Lu (2007), better-networked investors can help the startup get access to value-added services (e.g., introduce them to customers, suppliers, or strategic alliance partners.), so this could be one channel through which the CVC exposure increase the survival rate of startups. The implication of this table, however, should be interpreted with caution. It does not rule out the possibility that *More CVC Exposure* increases the startup survival through channels other than the investor centrality in current round. Therefore, we cannot conclude that CVCs impact startup survival only by introducing more centralized investors.

[Insert Table A5 around here.]

As stated above, Hochberg, Ljungqvist, and Lu (2007) find that better networked VCs are more successful both in fund performance and in the exits of their portfolio startups. The same thing could happen to CVCs. Do CVCs with different network profiles impact startup survival differently?

[14]Eigenvector centrality is a measure of the influence of a node in a network. It is different from degree centrality in that eigenvector centrality takes into consideration the importance of the connections in addition to the number of connections. To achieve this, eigenvector centrality is calculated as the sum of the ties to other co-investors weighted by the centrality of the corresponding co-investor.

For each observation, I collect all the M&As made by CVC parents in the past 12 month in the startup CBSA. To make sure that each parent is counted only once as proxy for CVC exposure, for each observation, I pick the most recent M&A for each parent and collect the eigenvector centrality of its CVC arm at the time of the M&A. Then, for each observation, I calculate the maximum eigenvector centrality across the potential CVCs (CVCs whose parents made M&A in the CBSA in th epast 12 month). Finally, for each observation, I repeat the same process but lag the transaction date for the observation by 12 months and get the maximum eigenvector centrality for last year.

To test the influence of CVC centrality on the relationship between CVC exposure and startup survival, I further partition the *More CVC Exposure* dummy into two dummies: *More CVC Exposure with Higher Centrality* (if *More CVC Exposure* is one, and maximum eigenvector centrality of the potential CVCs increases in the past 12 months) and *More CVC Exposure with Lower or Same Centrality* (if *More CVC Exposure* is one, and maximum eigenvector centrality of the potential CVCs does not increase in the past 12 months). I replace the CVC exposure dummy in Table 7 with these two new dummies and tabulate the results in Table A3 in Appendix. It shows that CVCs with different levels of network centrality impact startup survival differently. While exposure to all types of CVCs increase the probability of having a next round, only exposure to "cornered" CVCs who are new or less active can increase the probability of having a successful exit. Exposure to "star" CVCs that participate actively in the venture capital investments does not increase the probability of successful exit significantly. Put it in another way, more centralized "star" CVCs only increase survival of startups by increasing their probability of receiving another round.

[Insert Table A3 around here.]

It is worth mentioning that the outcome variable here is the round-level survival. So the results do not speak to the ultimate exit of the startup company. The interpretation should be that more centralized CVCs tend not to invest in the last round of a successful startup. Therefore, a possible explanation is that more centralized CVCs are more active and diversified in their investments, so that they may not facilitate an exit immediately after their investment. While less centralized "cornered" CVCs are limited in capital and more focused on their strategic investments, so they may rush to exit the startup. More detailed analyses are needed for further discussion.

6 Conclusions

This paper identifies the causal impact of CVC investors on the survival of startup companies. Using the stratified competing hazard model as well as a geographical based exogenous shock of CVC exposure, I find that exposure to CVCs increases the probability of having a next round and the probability of a successful exit subsequently. Although in the endogenous research design, CVCs are associated with a lower probability of having failed exit and next round, the analyses using exogenous CVC exposure shows no results for it, indicating the possible existence of selection in CVC investments. Follow on analyses shows that startups exposed to CVCs attract better-networked VC investors, which may be the channel through which CVCs increase the startup survival. I also show that the impact of CVC exposure differed for CVCs with different network characteristics.

There are some limitations in in the findings of the paper. First, the sample of the exogenous analyses is limited to CVCs with public parent firms and M&A deals with valid location information. Second, what I get from the model with exogenous shock is a local average treatment effect. Therefore, I cannot reject the hypothesis that the impact of CVCs on the probability of having a failed exit is zero. Third, none of the results from this paper speaks to the financial returns from the investment. "Successful exit" is defined as exiting by IPO, M&A or leverage buyout. There is no evidence about whether the investors get a higher return or not from the investment with or without CVC exposure.

This paper proves that there is a causal link between the CVC exposure and the survival of startup companies. Exposure to CVCs makes startups more likely to receive the next round and to exit successfully after the current round, regardless of their ultimate exits. This finding in startups' interim survival shows that the transaction-level analysis is plausible and useful. More importantly, the exogenous shock introduced by this paper can be applied to other questions in the venture capital research, such as the relationship between CVCs and innovation input, the relationship between CVCs and local job creation, etc.

References

Allison, Paul, 2002, Bias in fixed-effects cox regression with dummy variables, *Manuscript, Department of Sociology, University of Pennsylvania* 97.

Allison, Paul D, 1984, *Event history analysis: Regression for longitudinal event data* . No. 46 (Sage).

Axelson, Ulf, Per Strömberg, and Michael S Weisbach, 2009, Why are buyouts levered? the financial structure of private equity funds, *The Journal of Finance* 64, 1549–1582.

Barber, Brad M, and Ayako Yasuda, 2017, Interim fund performance and fundraising in private equity, *Journal of Financial Economics* 124, 172–194.

Bernstein, Shai, Xavier Giroud, and Richard R Townsend, 2016, The impact of venture capital monitoring, *The Journal of Finance* 71, 1591–1622.

Bonaccorsi di Patti, Emilia, and Giorgio Gobbi, 2001, The effects of bank consolidation and market entry on small business lending, Discussion paper, Bank of Italy, Economic Research and International Relations Area.

Chemmanur, Thomas J, and Zhaohui Chen, 2014, Venture capitalists versus angels: The dynamics of private firm financing contracts, *The Review of Corporate Finance Studies* 3, 39–86.

Chemmanur, Thomas J, Elena Loutskina, and Xuan Tian, 2014, Corporate venture capital, value creation, and innovation, *The Review of Financial Studies* 27, 2434–2473.

Cleves, Mario, William Gould, William W Gould, Roberto Gutierrez, and Yulia Marchenko, 2008, *An introduction to survival analysis using Stata* (Stata press).

Cole, Rebel A, and Lawrence J White, 2012, Déjà vu all over again: The causes of us commercial bank failures this time around, *Journal of Financial Services Research* 42, 5–29.

Cumming, Douglas J, and Samuele Murtinu, 2016, On the efficiency of bank-affiliated venture capital, in *FMA Conference Paper*.

Degryse, Hans, Nancy Masschelein, and Janet Mitchell, 2011, Staying, dropping, or switching: the impacts of bank mergers on small firms, *The Review of Financial Studies* 24, 1102–1140.

Derrien, François, and Ambrus Kecskés, 2013, The real effects of financial shocks: Evidence from exogenous changes in analyst coverage, *The Journal of Finance* 68, 1407–1440.

Di Patti, Emilia Bonaccorsi, and Giorgio Gobbi, 2007, Winners or losers? the effects of banking consolidation on corporate borrowers, *The Journal of Finance* 62, 669–695.

Du, Qianqian, and Thomas F Hellmann, 2019, Getting tired of your friends: The dynamics of venture capital relationships, Discussion paper, National Bureau of Economic Research.

Dushnitsky, Gary, and Michael J Lenox, 2005, When do incumbents learn from entrepreneurial ventures?: Corporate venture capital and investing firm innovation rates, *Research Policy* 34, 615–639.

——— , 2006, When does corporate venture capital investment create firm value?, *Journal of Business Venturing* 21, 753–772.

Ewens, Michael, Alexander S Gorbenko, and Arthur Korteweg, 2019, Venture capital contracts, Discussion paper, National Bureau of Economic Research.

Field, Laura, Michelle Lowry, and Anahit Mkrtchyan, 2013, Are busy boards detrimental?, *Journal of Financial Economics* 109, 63–82.

Goldfarb, Brent D, Gerard Hoberg, David Kirsch, and Alexander J Triantis, 2013, Are angels different? an analysis of early venture financing, *An Analysis of Early Venture Financing (November 4, 2013). Robert H. Smith School Research Paper No. RHS* pp. 06–072.

Gompers, Paul, and Josh Lerner, 2000, The determinants of corporate venture capital success: Organizational structure, incentives, and complementarities, in *Concentrated Corporate Ownership* . pp. 17–54 (University of Chicago Press).

——— , 2001, The venture capital revolution, *Journal of Economic Perspectives* 15, 145–168.

Gompers, Paul A, et al., 2002, Corporations and the financing of innovation: The corporate venturing experience, *Economic Review-Federal Reserve Bank of Atlanta* 87, 1–18.

Hellmann, Thomas, and Veikko Thiele, 2015, Friends or foes? the interrelationship between angel and venture capital markets, *Journal of Financial Economics* 115, 639–653.

Hochberg, Yael V, Laura A Lindsey, and Mark M Westerfield, 2015, Resource accumulation through economic ties: Evidence from venture capital, *Journal of Financial Economics* 118, 245–267.

Hochberg, Yael V, Alexander Ljungqvist, and Yang Lu, 2007, Whom you know matters: Venture capital networks and investment performance, *The Journal of Finance* 62, 251–301.

——— , 2010, Networking as a barrier to entry and the competitive supply of venture capital, *The Journal of Finance* 65, 829–859.

Ivanov, Vladimir I, and Fei Xie, 2010, Do corporate venture capitalists add value to start-up firms? evidence from ipos and acquisitions of vc-backed companies, *Financial Management* 39, 129–152.

Kim, E Han, and Vijay Singal, 1993, Mergers and market power: Evidence from the airline industry, *The American Economic Review* pp. 549–569.

Lerner, Joshua, 1994, The syndication of venture capital investments, *Financial Management* pp. 16–27.

Ma, Song, 2019, The life cycle of corporate venture capital, *The Review of Financial Studies* 33, 358–394.

Maula, Markku, Erkko Autio, and Gordon Murray, 2005, Corporate venture capitalists and independent venture capitalists: What do they know, who do they know and should entrepreneurs care?, *Venture Capital: An International Journal of Entrepreneurial Finance* 7, 3–21.

McCahery, Joseph A, and Erik PM Vermeulen, 2016, Venture capital 2.0: From venturing to partnering, *Lex Research Topics in Corporate Law & Economics Working Paper*.

Rosenstein, Joseph, Albert V Bruno, William D Bygrave, and Natalie T Taylor, 1993, The ceo, venture capitalists, and the board, *Journal of Business Venturing* 8, 99–113.

Shan, Hongyu, 2018, Corporate venture capital and the boundaries of the firm, in *2nd Emerging Trends in Entrepreneurial Finance Conference, 29th Annual Conference on Financial Economics & Accounting*.

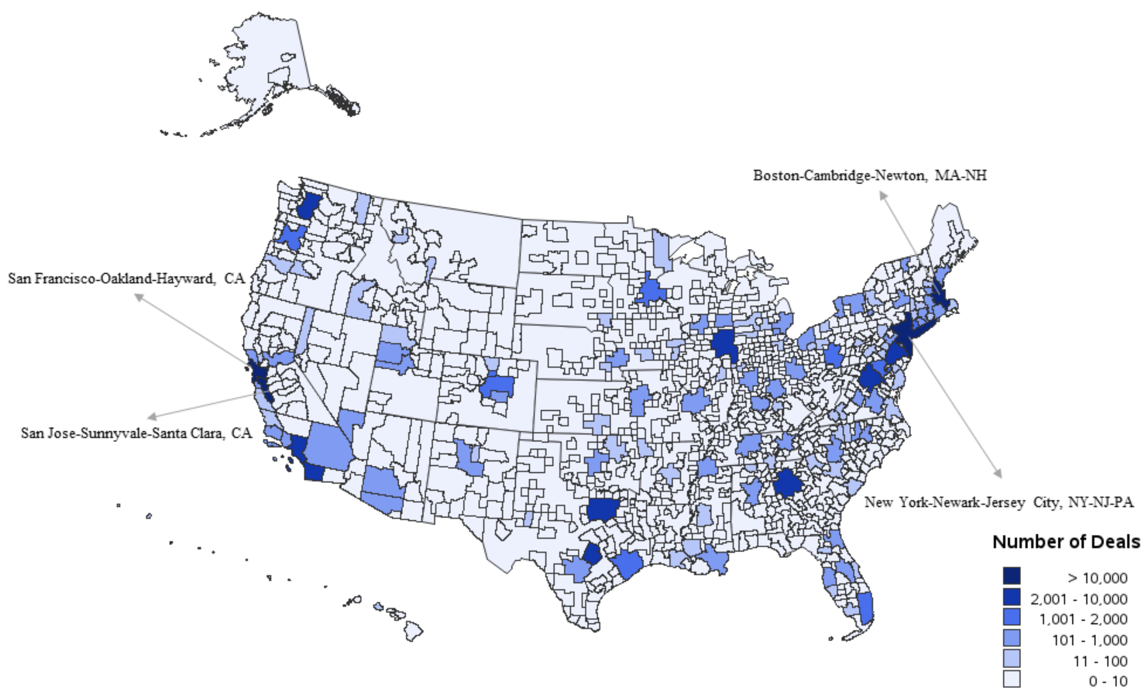
Sørensen, Morten, 2007, How smart is smart money? a two-sided matching model of venture capital, *The Journal of Finance* 62, 2725–2762.

Tian, Xuan, and Kailei Ye, 2020, A dark side of corporate venture capital, *Available at SSRN 3241866*.

Figure 1: Geographical Distribution of the Venture Capital Activities by CBSA

This figure shows the geographic distribution (by CBSA) of the sample deals (transactions) and sample startup companies in this paper. CBSA stands for "Core Based Statistical Area". It is the metropolitan and metropolitan statistical area delineation defined by the United States Office of Management and Budget (OMB). There are 939 CBSAs in total, including 392 MSAs (metropolitan statistical areas) and 547 μSAs (micropolitan statistical areas). Panel A is the heat-map of number of deals. The four CBSAs with the most number of deals are pointed out. Panel B is the heat-map of number of startup companies. The four CBSAs with the most number of startups are pointed out. More detailed information are presented in Table 3.

Panel A. Heat-map of Deals



Panel B. Heat-map of Startup Companies

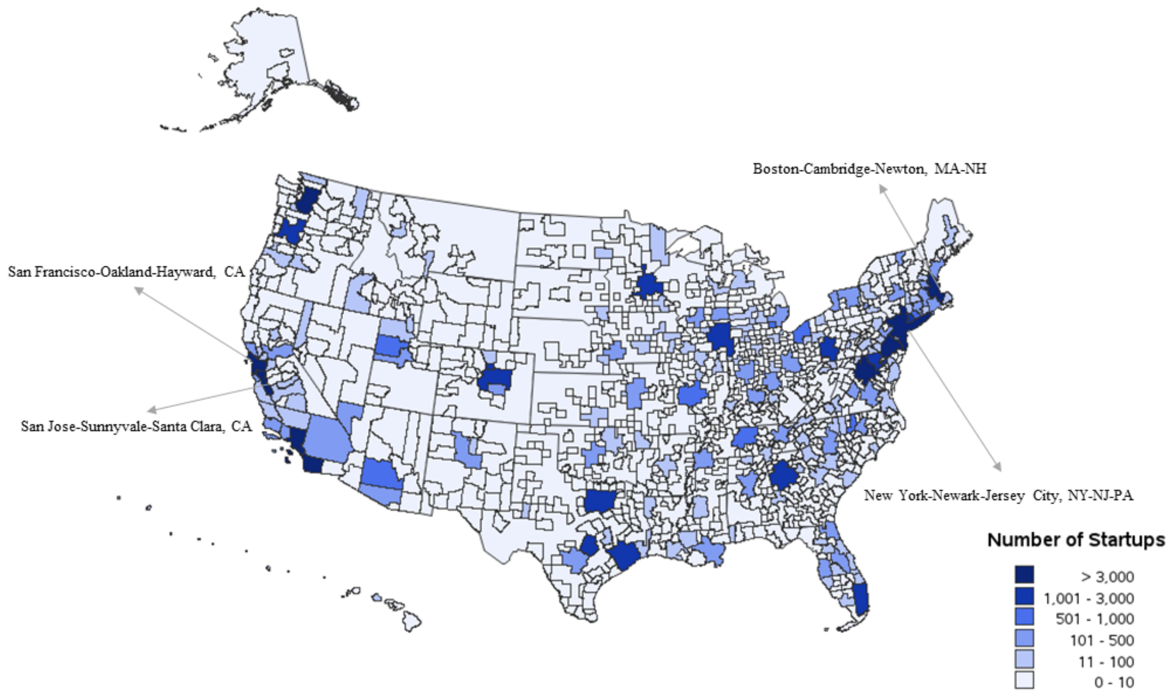


Figure 2: Industry Distributions of Treated Startups and M&A Targets

This figure shows the industry distributions (by VEIC1) of the treated startups and the target firm of corresponding M&As. VEIC1 stands for the sector level of venture economics industry classification. x-axis is the VEIC sectors of the treated startups. y-axis is the VEIC sectors of the corresponding M&A targets that trigger the treatment. Computer Software and Internet Specific standout as popular VC investments.

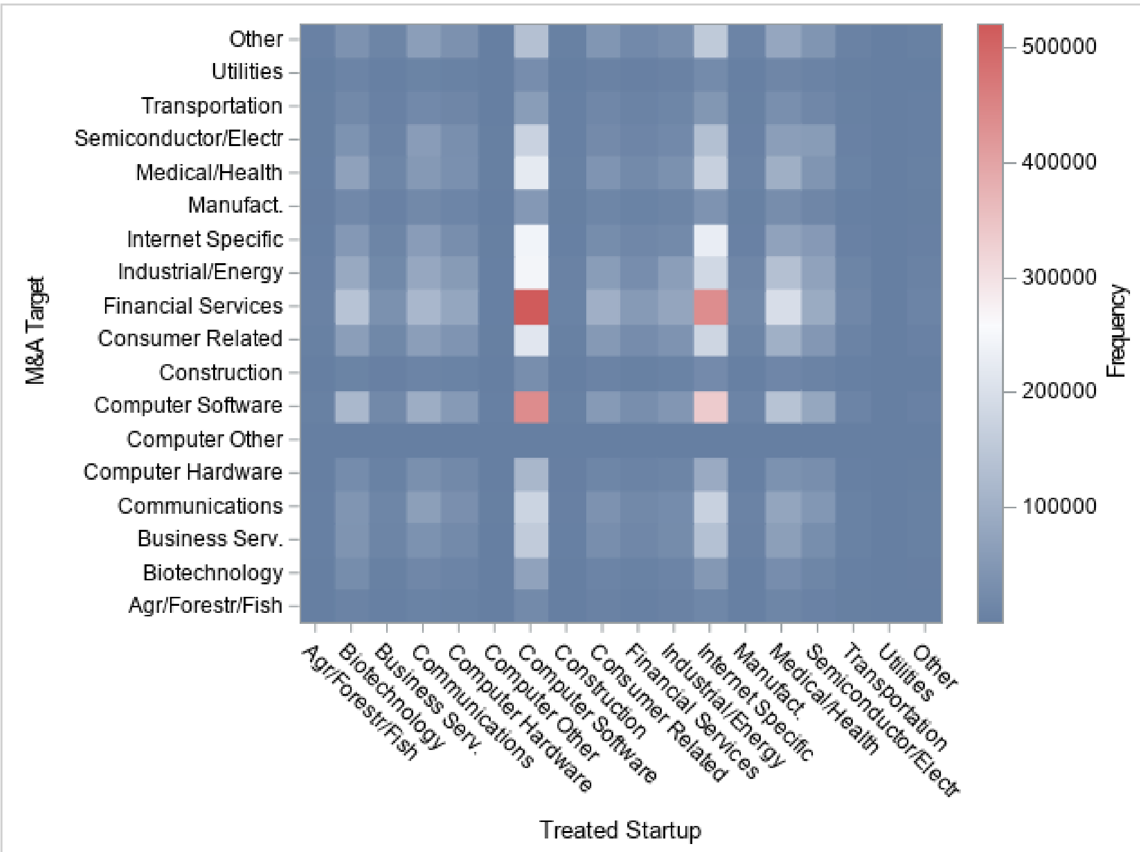
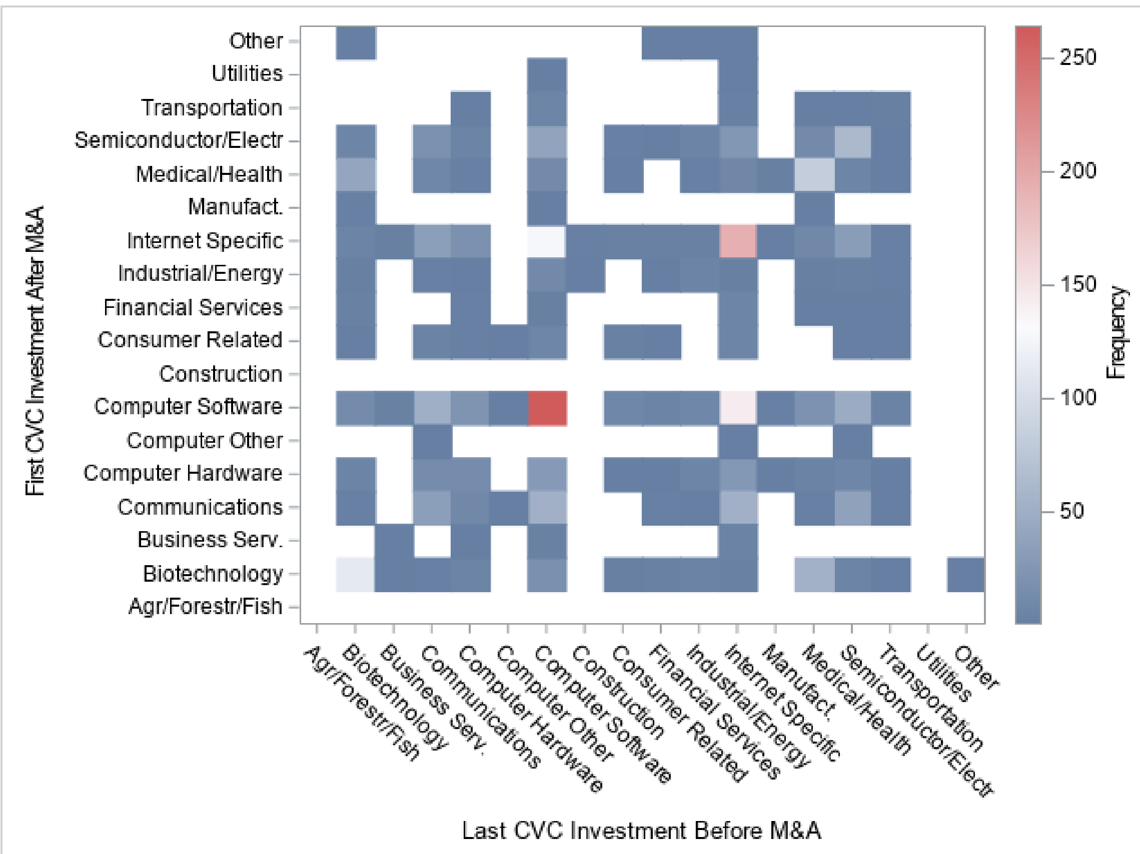


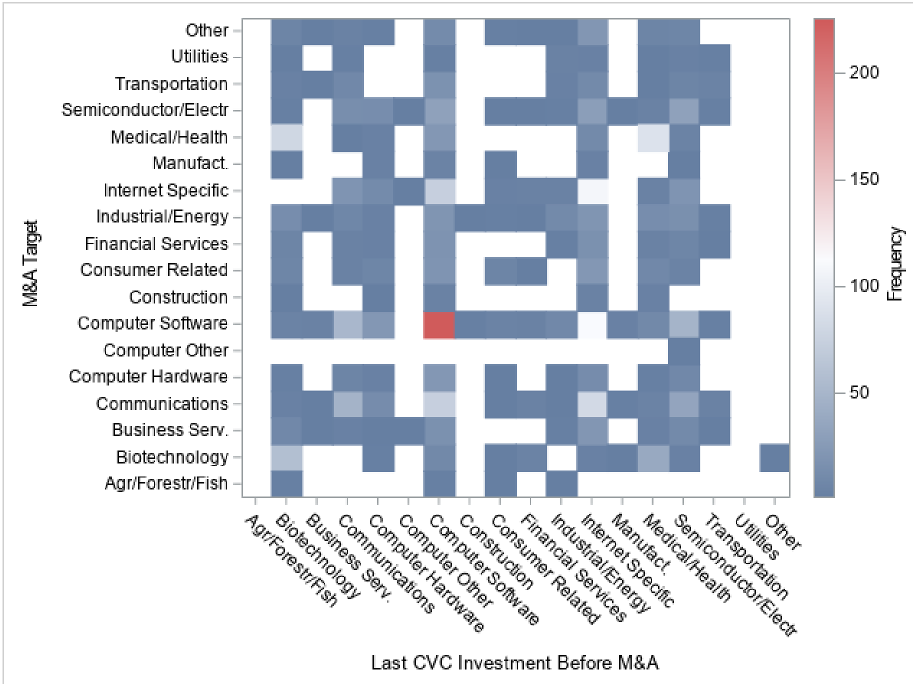
Figure 3: Industry Migrations of CVC-Parent Pairs

This figure shows the industry migrations (by VEIC1) of CVC parent firms and their CVC arms. VEIC1 stands for the sector level of venture economics industry classification. Panel A shows the industry migrations by comparing the CVC investments before and after an M&A. x-axis is the VEIC sectors of last CVC investment before the M&A. y-axis is the VEIC sectors of the first CVC investment after the M&A. To further decompose the migration. Panel B and Panel C compare the industry distributions of last CVC investments before M&A, M&A targets, and first CVC investments after M&A. There is no identifiable patterns on the diagonals except for Computer Software and Internet Specific sectors.

Panel A. Heat-map of Startup Companies



Panel B. Heat-map of Startup Companies



Panel C. Heat-map of Startup Companies

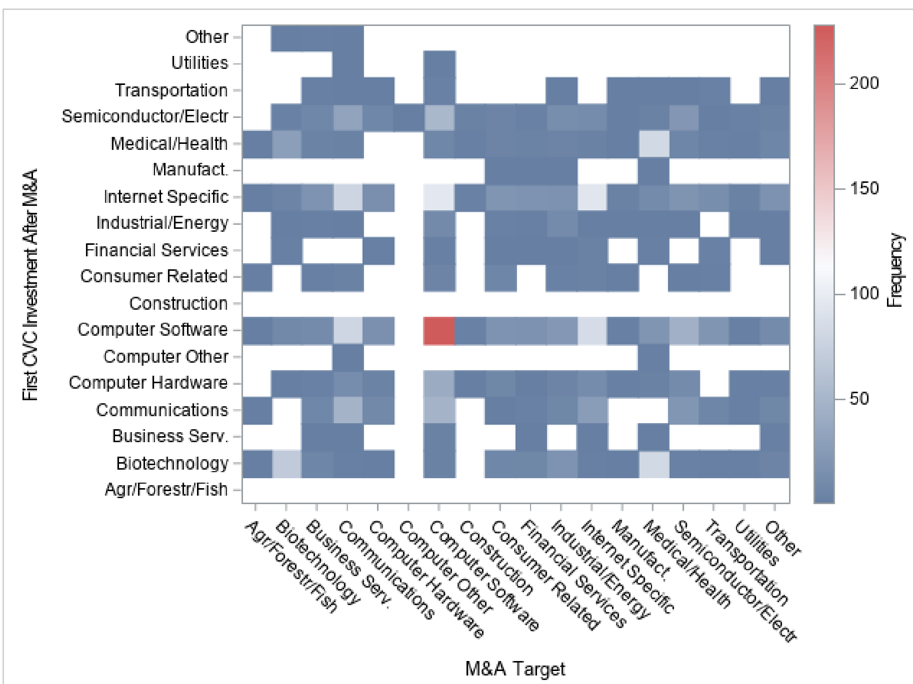


Table 1: Startup Company Summary Statistics

This table reports summary statistics at the startup company level. Data is from Refinitiv (former Thomson One VentureXpert) between 1962 and 2021. Panel A summarizes the investor composition of the startups. Panel B summarizes the industry distribution of the startups. Industry is defined based on VEIC (Venture Economics Industry Codes). VEIC2 (sub-sector) is used for all the tests in this paper. The table in Panel B presents the summary of VEIC1(sector) distribution. Panel C defines and summarizes exits and data censoring. *Successful Exit* is when a startup exits through IPO, M&A, or LBO. *Failed Exit* is when a startup is written off, or stays inactive for more than three years (following Tian and Ye (2020)). Whatever left are classified as *Censored*. Censored startups are not included in the startup-level analyses following the literature. Summaries of the industry sector and exit type are broke down into two groups based on whether the startup is backed by CVC. *Backed by CVC* is defined when at least one CVC investor invest in the startup before it exits.

Panel A. Investor Composition

	N	mean	sd	p1	p25	p50	p75	p99
Number of investors	111,021	2.600	2.594	1	1	2	3	13
Number of VCs	94,773	2.269	2.057	1	1	1	3	10
Number of CVCs	21,007	1.371	0.811	1	1	1	1	5
Number of BOs	9,829	1.101	0.364	1	1	1	1	3
Total number of rounds	111,021	2.018	1.679	1	1	1	2	9
log(Funding received)	89,236	2.188	1.459	0.036	0.970	2.014	3.191	6.082
log(Company age)	111,021	0.568	0.765	0	0	0	1.099	2.565
Observations	111,021							

Panel B. Industry Sector Distribution

	Backed by CVC?					
VEIC1 Code - Sector	No	%	Yes	%	Total	%
1000 - Communications	4,046	77.90	1,148	22.10	5,194	4.68
2100 - Computer Hardware	3,394	77.03	1,012	22.97	4,406	3.97
2700 - Computer Software	21,183	77.35	6,204	22.65	27,387	24.67
2800 - Internet Specific	17,898	77.69	5,140	22.31	23,038	20.75
2900 - Computer Other	118	81.94	26	18.06	144	0.13
3000 - Semiconductor/Electronic	4,074	75.18	1,345	24.82	5,419	4.88
4000 - Biotechnology	4,164	71.78	1,637	28.22	5,801	5.23
5000 - Medical/Health	6,787	81.93	1,497	18.07	8,284	7.46
7000 - Consumer Related	7,886	91.53	730	8.47	8,616	7.76
8000 - Industrial/Energy	6,557	86.46	1,027	13.54	7,584	6.83
9000 - Transportation	1,706	88.17	229	11.83	1,935	1.74
9200 - Financial Services	4,324	91.65	394	8.35	4,718	4.25
9300 - Business Service	3,046	91.69	276	8.31	3,322	2.99
9400 - Manufactory	1,689	92.65	134	7.35	1,823	1.64
9500 - Agriculture/Forestry/Fish	967	93.88	63	6.12	1,030	0.93
9700 - Construction	912	94.41	54	5.59	966	0.87
9800 - Utilities	233	92.09	20	7.91	253	0.23
9900 - Other	1,030	93.55	71	6.45	1,101	0.99
Total	90,014	81.08	21,007	18.92	111,021	100

Panel C. Exit Type

	Not Backed by CVC	Backed by CVC	Total
Successful Exit:			
IPO	2,640	1,119	3,759
M&A	10,225	3,360	13,585
LBO	1,370	178	1,548
Failed Exit:			
Write Off	963	302	1,265
Inactive $\geq$ 3 years	55,536	8,865	64,401
Censored:			
Inactive $<$ 3 years	19,280	7,183	26,463
Total	90,014	21,007	111,021

Table 2: Transaction Round Summary Statistics

This table reports summary statistics at the transaction (round) level. Data is from Refinitiv (former Thomson One VentureXpert) between 1962 and 2021. Every observation is one round of investment received by one startup company. *Number of investors*, *Number of VCs* and *Number of CVCs* are the counts of all investors, VC investors, and CVC investors in that round, respectively. *Buyout investors present* is set to be one if an buyout investors invest in that round. *Survive this round* is a dummy that equal one if the startup has a next round or exit successfully right after this round and zero otherwise. *log(Deal Value)* is the nature logarithm of deal value in millions USD. *log(Company age)* is the natural logarithm of number of years since the first investment date of the startup. Panel A is the summary of full sample. Panel B is the summary of rounds with CVCs present. Panel C is the summary of rounds without CVCs present.

Panel A. Full Sample

	N	mean	sd	p1	p25	p50	p75	p99
Number of investors	236,186	2.109	1.788	1	1	1	3	9
Number of VCs	236,186	1.639	1.504	0	1	1	2	7
Number of CVCs	236,186	0.181	0.489	0	0	0	0	2
Buyout investors present	236,186	0.070	0.254	0	0	0	0	1
Survive this round	236,186	0.610	0.488	0	0	1	1	1
log(Deal Value)	195,122	1.649	1.186	0.025	0.693	1.465	2.398	5.090
log(Company age)	236,186	0.661	0.763	0	0	0	1.386	2.565
Round number	236,186	2.370	2.052	1	1	2	3	10

Panel B. CVCs Present

	N	mean	sd	p1	p25	p50	p75	p99
Number of investors	34,969	3.674	2.654	1	2	3	5	12
Number of VCs	34,969	2.122	2.193	0	0	2	3	9
Number of CVCs	34,969	1.224	0.581	1	1	1	1	4
Buyout investors present	34,969	0.062	0.241	0	0	0	0	1
Survive this round	34,969	0.630	0.483	0	0	1	1	1
log(Deal Value)	29,540	2.336	1.212	0.114	1.386	2.322	3.157	5.090
log(Company age)	34,969	0.814	0.766	0	0	0.693	1.386	2.565
Round number	34,969	2.653	2.024	1	1	2	3	10

Panel C. No CVCs Present

	N	mean	sd	p1	p25	p50	p75	p99
Number of investors	201,217	1.837	1.424	1	1	1	2	7
Number of VCs	201,217	1.555	1.331	0	1	1	2	6
Number of CVCs	201,217	0	0	0	0	0	0	0
Buyout investors present	201,217	0.071	0.257	0	0	0	0	1
Survive this round	201,217	0.606	0.489	0	0	1	1	1
log(Deal Value)	165,582	1.526	1.139	0.025	0.588	1.361	2.250	4.943
log(Company age)	201,217	0.635	0.760	0	0	0	1.099	2.565
Round number	201,217	2.321	2.053	1	1	2	3	10

Table 3: Venture Capital Activities by CBSAs

This table lists the top 30 VC-active CBSAs (core-based statistical areas) ranked by number of venture capital transactions (rounds). Startup companies located in the US are linked to CBSA using their ZIP codes with the link table provided by Stanford Center for Population Health Science. CBSAs in this table are ranked by the number of venture capital transactions (*Number of Deals*) happen in the location between 1980 and 2020. *Number of Startups* is the number of unique startup companies in that location throughout the sample period.

Rank - CBSA Title	CBSA Code	Number of Deals	Number of Startups
01-San Francisco-Oakland-Hayward, CA	41860	19,304	7,003
02-San Jose-Sunnyvale-Santa Clara, CA	41940	14,039	4,465
03-Boston-Cambridge-Newton, MA-NH	14460	12,975	4,079
04-New York-Newark-Jersey City, NY-NJ-PA	35620	10,622	4,690
05-Los Angeles-Long Beach-Anaheim, CA	31080	6,882	2,883
06-Washington-Arlington-Alexandria, DC-VA-MD-WV	47900	4,009	1,595
07-San Diego-Carlsbad, CA	41740	3,824	1,228
08-Seattle-Tacoma-Bellevue, WA	42660	3,597	1,322
09-Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	37980	3,192	1,323
10-Chicago-Naperville-Elgin, IL-IN-WI	16980	2,844	1,221
11-Austin-Round Rock, TX	12420	2,630	948
12-Atlanta-Sandy Springs-Roswell, GA	12060	2,506	971
13-Dallas-Fort Worth-Arlington, TX	19100	2,382	958
14-Denver-Aurora-Lakewood, CO	19740	1,921	716
15-Minneapolis-St. Paul-Bloomington, MN-WI	33460	1,762	678
16-Pittsburgh, PA	38300	1,531	566
17-Houston-The Woodlands-Sugar Land, TX	26420	1,383	625
18-Boulder, CO	14500	1,159	372
19-Portland-Vancouver-Hillsboro, OR-WA	38900	1,154	429
20-Bridgeport-Stamford-Norwalk, CT	14860	1,098	428
21-Baltimore-Columbia-Towson, MD	12580	1,057	466
22-Miami-Fort Lauderdale-West Palm Beach, FL	33100	1,050	527
23-Phoenix-Mesa-Scottsdale, AZ	38060	936	345
24-Salt Lake City, UT	41620	803	300
25-Nashville-Davidson–Murfreesboro–Franklin, TN	34980	793	329
26-New Haven-Milford, CT	35300	655	198
27-St. Louis, MO-IL	41180	626	253
28-Cleveland-Elyria, OH	17460	617	254
29-Durham-Chapel Hill, NC	20500	581	186
30-Ann Arbor, MI	11460	507	201

Table 4: Geographical Proximity and CVC Transactions

This table reports the validation tests of the CVC exposure proxy. Each observation is a CVC parent pair-CBSA-year combination. The sample period is 1980 to 2020. In columns (1) and (3), only investment-active CBSAs are kept (CBSAs that have less than 100 venture capital deals in the sample years are dropped). In columns (3) and (4), I keep all the CBSAs. Dependent variable in columns (1) and (2) is *CVC Makes Deals*, a dummy that equals one if the CVC in pair x make venture capital investment in CBSA y in year z, and equals zero otherwise. Independent variable is *Parent Makes M&As*, a dummy that equals one if parent in pair x do M&A in CBSA y in year z-1, and equals zero otherwise. Panel B repeat the tests with an alternative M&A window of past three years. All the regressions are controlled for pair, year, and CBSA fixed effect. Standard errors in columns (2) and (4) are clustered at the CBSA level.

Panel A. CVC Transactions and Parent M&A in Last Year

	(1)	(2)	(3)	(4)
	CVC Makes Deals		CVC Makes More Deals	
Parent Makes M&As	0.119***	0.122***		
	(5.67)	(5.65)		
Parent Makes More M&As			0.072***	0.074***
			(4.38)	(4.37)
Geographical Diversity of CVC	0.014***	0.002***	0.008***	0.001***
	(5.06)	(4.61)	(5.82)	(5.18)
Observations	342,675	2,279,931	307,875	2,048,395
R-squared	0.12	0.11	0.07	0.06
Fixed Effect	Pair + Year + CBSA	Pair + Year + CBSA	Pair + Year + CBSA	Pair + Year + CBSA
Cluster	CBSA	CBSA	CBSA	CBSA

Panel B. CVC Transactions and Parent M&A in Past Three Years

	(1)	(2)	(3)	(4)
	CVC Makes Deals		CVC Makes More Deals	
Parent Makes M&As	0.095***	0.096***		
	(4.00)	(4.00)		
Parent Makes More M&As			0.073***	0.076***
			(4.68)	(4.74)
Geographical Diversity of CVC	0.016***	0.003***	0.008***	0.001***
	(4.86)	(4.45)	(5.95)	(5.22)
Observations	273,750	1,821,350	246,450	1,639,714
R-squared	0.13	0.11	0.07	0.06
Fixed Effect	Pair + Year + CBSA	Pair + Year + CBSA	Pair + Year + CBSA	Pair + Year + CBSA
Cluster	CBSA	CBSA	CBSA	CBSA

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Transaction Round Survival and CVC

This table tests the correlation between CVCs and startups' round-level survival. Every observation is one round of investment received by one startup company. Any M&A or LBO round that serves as an exit is dropped from the sample. Panel A is the univariate test. *Does Not Survive* is when a startup round is followed by a failed exit (being written-off or being inactive for more than three years). *Survive This Round* is when a startup has a successful exit subsequent to the current round or when the startup has a next round. Numbers in this panel are the counts of transactions (rounds) in each category. Numbers in the bracket are the column percentages (e.g., in column (2), they are percentage of not survive/survive conditional on having CVCs in this round). Number in the third column is the difference in survive rate with and without having CVCs in the current round. Panel B is OLS regression. Dependent variable is a dummy that equals one if the startup company survive the current round. *CVCs (VCs/Buyout investors) present* equals one if there is at least one CVC (VC/buyout investor) making investment in this round. *Deal Value* is the total dollar value of this investment measured in millions USD. *Company Age* is the number of years since the startup receives its first investment. Any missing first investment date is supplemented with the first observed transaction date of the startup company. I take the log of *Deal Value* and *Company Age* to address the skewness in the distributions. Columns (1), (3) and (5) have industry and transaction year fixed effect. Columns (2), (4) and (6) have industry and round number fixed effect. All the models are clustered at the industry level. Industry of the startups are defined by VEIC2 (sub-secotr).

Panel A. Univariate Test

	(1) No VC No CVC Freq. (Perc.%)	(2) No VC With CVC Freq. (Perc.%)	(3) Diff. in Perc. (2)-(1)	(4) With VC No CVC Freq. (Perc.%)	(5) With VC With CVC Freq. (Perc.%)	(6) Diff. in Perc. (5)-(4)
Does Not Survive	11,662	4,954		67,527	7,986	
	(52.96)	(50.26)		(37.68)	(31.80)	
Survives This Round	10,358	4,902		111,670	17,127	
	(47.04)	(49.74)	(2.7***)	(62.32)	(68.20)	(5.88***)
			t = 4.45			t=18.65
Total	22,020	9,856		179,197	25,113	

Panel B. OLS Regression

	(1)	(2)	(3)	(4)	(5)	(6)
			Survive This Round			
CVCs present	0.075***	0.075***	0.079***	0.079***	0.023***	0.023***
	(28.05)	(11.84)	(29.61)	(10.49)	(8.08)	(3.07)
VCs present	0.138***	0.138***	0.161***	0.161***	0.107***	0.107***
	(49.90)	(24.85)	(55.59)	(32.47)	(32.46)	(10.59)
Buyout investors present			0.101***	0.101***	0.034***	0.034**
			(26.08)	(7.05)	(8.18)	(2.18)
log(Deal Value)					0.050***	0.050***
					(52.05)	(12.39)
log(Company age)					0.012***	0.012***
					(5.61)	(2.75)
Round number					0.019***	0.019***
					(26.35)	(13.00)
Observations	236,186	236,186	236,186	236,186	195,122	195,122
R-squared	0.17	0.17	0.17	0.17	0.20	0.20
Fixed Effect	Ind + Year	Ind + Year	Ind + Year	Ind + Year	Ind + Year	Ind + Year
Cluster		Industry		Industry		Industry

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Cause-specific Survival Analysis

This table reports the results of stratified competing hazard regression. Even columns report the marginal effect of each variable on the odds of each outcomes. Odd columns show the corresponding t-stats. The three outcomes are defined as follow: *Next Round* is the outcome when a startup has a next round (if its not being written off or being inactive for more than three years subsequent to the current round). *Successful Exit* is the outcome when a startup exit successfully (through IPO, M&A or LBO) subsequent to the current round. *Failed Exit* is the outcome when a round is followed by a failed exit (being written-off or being inactive for more than three years). *log(Deal Value)* is the nature logarithm of deal value in millions USD. *log(Company age)* is the natural logarithm of number of years since the startup receives its first investment. All the regressions are stratified by startup industry, transaction year and outcome. Standard errors are clustered at the startup industry level.

	(1)		(2)		(3)	
	Marginal Effect	t-stat	Marginal Effect	t-stat	Marginal Effect	t-stat
CVCs Present						
Next Round	-0.056***	(-4.86)	-0.041***	(-3.65)	-0.041***	(-3.71)
Successful Exit	0.159***	(7.18)	0.198***	(9.69)	0.203***	(9.85)
Failed Exit	-0.025***	(-2.66)	-0.048***	(-4.40)	-0.053***	(-4.46)
VCs Present						
Next Round			0.111***	(5.41)	0.112***	(4.83)
Successful Exit			0.269***	(7.75)	0.300***	(9.37)
Failed Exit			-0.090***	(-13.54)	-0.105***	(-12.98)
Buyout Investors Present						
Next Round					0.004	(0.13)
Successful Exit					0.089**	(2.03)
Failed Exit					-0.065***	(-3.16)
log(Deal Value)	-0.080***	(-11.99)	-0.083***	(-11.79)	-0.082***	(-12.68)
log(Company age)	-0.447***	(-15.96)	-0.451***	(-16.35)	-0.451***	(-16.44)
Round number	0.058***	(13.10)	0.057***	(13.09)	0.057***	(13.03)
Observations	192,637		192,637		192,637	
Pseudo R-squared	0.0053		0.0055		0.0055	
Strata	Ind + Year + Outcome		Ind + Year + Outcome		Ind + Year + Outcome	
Cluster	Industry		Industry		Industry	

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Cause-specific Survival Analysis with Exogenous Shock

This table reports the results of stratified competing hazard regression with the exogenous CVC exposure proxy. Even columns report the marginal effect of each variable on the odds of each outcomes. Odd columns are the corresponding t-stats. The three outcomes are defined as follow: *Next Round* is the outcome when a startup has a next round (if its not being written off or being inactive for more than three years subsequent to the current round). *Successful Exit* is the outcome when a startup exit successfully (through IPO, M&A or LBO) subsequent to the current round. *Failed Exit* is the outcome when a round is followed by a failed exit (being written-off or being inactive for more than three years). *More CVC Exposure* is a dummy that equals one if the number CVC parent doing M&As in the CBSA increases in the past 12 months. *More M&A Activities* is a dummy that equals one if the number of all the M&As in the CBSA increases in the past 12 months. *log(Deal Value)* is the nature logarithm of deal value in millions USD. *log(Company age)* is the natural logarithm of number of years since the startup receives its first investment. *Round Number* is the round number in sequence of the transaction (if its the first round then *Round Number* is one; if its the seond round, then *Round Number* is two). All the regressions are stratified by startup industry, transaction year and outcome. Standard errors are clustered at the startup industry level.

	(1)		(2)		(3)	
	Marginal Effect	t-stat	Marginal Effect	t-stat	Marginal Effect	t-stat
More CVC Exposure						
Next Round	0.024***	(3.20)	0.023***	(3.11)	0.023***	(3.11)
Successful Exit	0.070***	(3.94)	0.066***	(3.81)	0.066***	(3.82)
Failed Exit	-0.005	(-0.51)	-0.002	(-0.23)	-0.002	(-0.23)
VCs Present						
Next Round			0.129***	(3.85)	0.130***	(3.67)
Successful Exit			0.268***	(5.49)	0.258***	(5.30)
Failed Exit			-0.087***	(-7.78)	-0.095***	(-8.13)
Buyout Investors Present						
Next Round					0.006	(0.19)
Successful Exit					-0.027	(-0.52)
Failed Exit					-0.032	(-1.29)
More M&A Activities						
Next Round	0.007	(0.89)	0.007	(0.85)	0.007	(0.84)
Successful Exit	0.042***	(2.78)	0.038**	(2.45)	0.038**	(2.42)
Failed Exit	-0.007	(-0.58)	-0.007	(-0.58)	-0.007	(-0.60)
log(Deal Value)	-0.123***	(-15.73)	-0.127***	(-16.80)	-0.127***	(-17.82)
log(Company age)	-0.435***	(-21.58)	-0.439***	(-22.43)	-0.439***	(-22.70)
Round number	0.045***	(11.26)	0.044***	(11.35)	0.044***	(11.28)
Observations	110,513		110,513		110,513	
Pseudo R-squared	0.0067		0.0069		0.0069	
Strata	Ind + Year + Outcome		Ind + Year + Outcome		Ind + Year + Outcome	
Cluster	Industry		Industry		Industry	

t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Cause-specific Survival Analysis with Exogenous Shock - Excluding M&A in the Same Industry

This table reports the results of stratified competing hazard regression with CVC exposure proxy calculated in an alternative way as compared to Table 7. Even columns report the marginal effect of each variable on the odds of each outcomes. Odd columns are the corresponding t-stats. The three outcomes and the three control variables (*log(Deal Value)*, *log(Company age)*, *Round Number)* are defined in the same way as in Table 7. *More CVC Exposure* is a dummy that equals one if the number of CVC parents doing M&As outside of the startup industry in the CBSA increases in the past 12 months. *More M&A Activities* is a dummy that equals one if the number of all the M&As outside of the startup industry in the CBSA increases in the past 12 months. All the regressions are stratified by startup industry, transaction year and outcome. Standard errors are clustered at the startup industry level.

	(1) Marginal Effect	t-stat	(2) Marginal Effect	t-stat	(3) Marginal Effect	t-stat
More CVC Exposure						
Next Round	0.029***	(3.41)	0.028***	(3.30)	0.028***	(3.30)
Successful Exit	0.070***	(4.01)	0.064***	(3.94)	0.064***	(3.95)
Failed Exit	-0.009	(-1.03)	-0.007	(-0.75)	-0.007	(-0.75)
VCs Present						
Next Round			0.128***	(3.84)	0.130***	(3.66)
Successful Exit			0.266***	(5.45)	0.256***	(5.27)
Failed Exit			-0.087***	(-7.76)	-0.095***	(-8.09)
Buyout Investors Present						
Next Round					0.006	(0.19)
Successful Exit					-0.028	(-0.54)
Failed Exit					-0.032	(-1.29)
More M&A Activities						
Next Round	0.002	(0.21)	0.001	(0.15)	0.001	(0.15)
Successful Exit	0.058**	(2.15)	0.054**	(2.17)	0.054**	(2.14)
Failed Exit	-0.011	(-0.88)	-0.010	(-0.83)	-0.010	(-0.85)
log(Deal Value)	-0.123***	(-15.81)	-0.127***	(-16.87)	-0.127***	(-17.89)
log(Company age)	-0.435***	(-21.57)	-0.439***	(-22.41)	-0.439***	(-22.68)
Round Number	0.045***	(11.25)	0.044***	(11.34)	0.044***	(11.26)
Observations	110,513		110,513		110,513	
Pseudo R-squared	0.0067		0.0069		0.0069	
Strata	Ind + Year + Outcome		Ind + Year + Outcome		Ind + Year + Outcome	
Cluster	Industry		Industry		Industry	

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Cause-specific Survival Analysis with Exogenous Shock - Separate Exit Type

This table reports the results of stratified competing hazard regression with the exogenous CVC exposure proxy calculated in the same as in Table 8 but with more granular outcome classifications. Even columns report the marginal effect of each variable on the odds of each outcomes. Odd columns are the corresponding t-stats. *More CVC Exposure* is a dummy that equals one if the number of CVC parents doing M&As outside of the startup industry in the CBSA increases in the past 12 months. *More M&A Activities* is a dummy that equals one if the number of all the M&As outside of the startup industry in the CBSA increases in the past 12 months. All the regressions are stratified by startup industry, transaction year and outcome. Standard errors are clustered at the startup industry level.

	(1)		(2)		(3)	
	Marginal Effect	t-stat	Marginal Effect	t-stat	Marginal Effect	t-stat
More CVC Exposure						
Next Round	0.030***	(3.45)	0.029***	(3.33)	0.029***	(3.33)
M&A Exit	0.052*	(1.87)	0.047*	(1.86)	0.047*	(1.88)
LBO Exit	0.146	(1.44)	0.170*	(1.77)	0.173*	(1.80)
IPO Exit	-0.014	(-0.24)	-0.015	(-0.26)	-0.007	(-0.13)
Failed Exit	-0.009	(-0.97)	-0.006	(-0.70)	-0.006	(-0.70)
VCs Present						
Next Round			0.133***	(3.93)	0.135***	(3.79)
M&A Exit			0.253***	(5.56)	0.236***	(5.09)
LBO Exit			-0.358	(-1.45)	-0.318	(-1.00)
IPO Exit			-0.172	(-0.59)	-0.346	(-1.00)
Failed Exit			-0.085***	(-7.55)	-0.092***	(-7.80)
Buyout Investors Present						
Next Round					0.009	(0.29)
M&A Exit					-0.048	(-0.73)
LBO Exit					0.073	(0.24)
IPO Exit					-0.462**	(-2.51)
Failed Exit					-0.028	(-1.14)
More M&A Activities						
Next Round	0.002	(0.23)	0.001	(0.16)	0.001	(0.17)
M&A Exit	0.025	(0.78)	0.024	(0.79)	0.023	(0.76)
LBO Exit	-0.072	(-0.73)	-0.054	(-0.55)	-0.055	(-0.56)
IPO Exit	0.002	(0.02)	0.005	(0.06)	0.027	(0.34)
Failed Exit	-0.010	(-0.87)	-0.010	(-0.82)	-0.010	(-0.84)
log(Deal Value)	-0.126***	(-16.78)	-0.130***	(-17.92)	-0.130***	(-18.98)
log(Company age)	-0.449***	(-20.82)	-0.454***	(-21.60)	-0.454***	(-21.83)
Round Number	0.044***	(10.93)	0.044***	(11.02)	0.044***	(10.93)
Observations	110,513		110,513		110,513	
Pseudo R-squared	0.0071		0.0073		0.0073	
Strata	Ind + Year + Outcome		Ind + Year + Outcome		Ind + Year + Outcome	
Cluster	Industry		Industry		Industry	

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendices

Appendix A Treatment for Duplicate Data

Investors and startup companies are identified using unique IDs in VentureXpert. However, some investors/startups are assigned different IDs even if they are actually the same one. (For example, "TeleSoft SA (ID 4296642087)" and "Telesoft SA (ID 4296654513)" are exactly the same company). To address this problem, I implement the following treatment:

1. If an investor name is associated with only one ID, then there is no duplication.

2. In very rare cases, if an investor name is associated with more than two ($\geq$3) IDs, then I manually check to see if they are the same one.

3. If an investor name is associated with two IDs, then I observe the investment windows of the two investors/startups.

(i) if there are overlaps between the two investment windows, and their addresses (if missing addresses, compare the cities) are the same, they will be viewed as the same investor;

(ii) if the gap between their investment windows is less than ten years and their addresses (if missing addresses, compare the cities) are the same, they will be viewed as the same investor.

4. For startup companies, I repeat the same steps but change the restriction in step 3 (ii) from ten years to three years to match the definition for written-off in the exit data treatment.

Appendix B Additional Tables

Table A1: Successful Exit and CVC

This table tests the correlation between CVCs and successful exits at the startup company level. It is a replication of previous literature (Gompers and Lerner 2000; Gompers et al. 2002; Ivanov and Xie 2010; Chemmanur and Chen 2014). Panel A is the univariate test. *Failed Exit* is when the startup is written off or is inactive for more than three years by the end of 2021. *Successful Exit* is when a startup exit ultimately through IPO, M&A, or LBO (as classified in Panel C of Table 1). Any startup that is inactive for less than three years are regarded as censored and are not included in this analysis. Numbers in this panel are the counts of startups in each category. Numbers in the bracket are the column percentages (e.g., in column (2), they are percentages of failed/successful exit conditional on being backed by CVCs). Number in the third column is the difference in successful exit rate with and without being backed by CVCs. Panel B is OLS regression. Dependent variable is a dummy that equals one if the startup company has a successful exit. *Backed by CVCs (VCs/BOs)* equals one if a startup is invested by at least one CVC (VC/buyout investor) before its exit. *Total number of rounds* is the total number of investment rounds a startup has before its exit. *Company Age* is defined as number of years between the date when the startup receive its first investment and the exit year. *Funding Received* is the total funding received by the startup company by the time it exits in USD. I take the log of *Funding Received* and *Company Age* to address the skewness in the distribution. Fixed effects are startup industry and first investment year. Column (2), (4) and (6) are clustered at the startup industry level. Industry is defined by VEIC2 (sub-sector).

Panel A. Univariate Test

	(1) Not backed by CVCs Freq. (Perc.%)	(2) Backed by CVCs Freq. (Perc.%)	(3) Diff in Perc. (2)-(1)
Failed Exit	56,499	9,167	
	(79.88)	(66.31)	
Successful Exit	14,235	4,657	
	(20.12)	(33.69)	(13.56***)
			t = 31.59
Total	70,734	13,824	

Panel B. OLS Regression

	(1)	(2)	(3)	(4)	(5)	(6)
			Successful Exit			
Backed by CVCs	0.083***	0.083***	0.030***	0.030***	0.029***	0.029***
	(21.19)	(11.87)	(6.84)	(4.83)	(6.64)	(4.63)
Backed by VCs	0.089***	0.089***	0.046***	0.046***	0.044***	0.044***
	(21.92)	(9.95)	(9.43)	(5.84)	(9.02)	(5.90)
Backed by BOs	0.121***	0.121***	0.040***	0.040***	0.039***	0.039***
	(24.83)	(18.58)	(7.21)	(4.88)	(7.02)	(4.81)
Total number of rounds	0.038***	0.038***	0.008***	0.008***	0.003**	0.003
	(42.61)	(9.43)	(8.17)	(3.02)	(2.47)	(1.55)
log(Funding Received)			0.084***	0.084***	0.083***	0.083***
			(61.79)	(12.43)	(59.83)	(12.66)
log(Company age)					0.017***	0.017**
					(5.33)	(2.63)
Observations	84,558	84,558	67,961	67,961	67,961	67,961
R-squared	0.11	0.11	0.16	0.16	0.16	0.16
Fixed Effect	Ind + Year	Ind + Year	Ind + Year	Ind + Year	Ind + Year	Ind + Year
Cluster	-	Industry	-	Industry	-	Industry

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2: Investors Composition in Current Round with M&A Shock

This table tests the investor compositions in the current round with the exogenous CVC shock. In columns (1) and (2), dependent variable is the number of all investors. In columns (3) and (4), dependent variable is the number of VC investors. In columns (5) and (6), dependent variable is the number of CVC investors. All the regressions have industry and year fixed effects. Columns (2), (4) and (6) are clustered at the startup industry level, which is defined by VEIC2 (sub-secotr).

	(1)	(2)	(3)	(4)	(5)	(6)
	Number of Investors (this round)		Number of VCs (this round)		Number of CVCs (this round)	
More CVC Exposure	-0.012	-0.012	0.008	0.008	0.008*	0.008**
	(-0.83)	(-1.00)	(0.70)	(0.81)	(1.77)	(2.04)
More M&A Activities	0.050***	0.050***	0.051***	0.051***	0.013***	0.013***
	(3.46)	(3.45)	(4.11)	(4.18)	(2.90)	(3.14)
log(Deal Value)	0.886***	0.886***	0.675***	0.675***	0.132***	0.132***
	(139.12)	(20.91)	(125.64)	(19.43)	(65.57)	(20.90)
log(Company age)	-0.150***	-0.150***	-0.125***	-0.125***	-0.005	-0.005
	(-10.10)	(-8.48)	(-9.93)	(-7.81)	(-1.02)	(-0.77)
Round number	0.045***	0.045***	0.041***	0.041***	0.001	0.001
	(11.83)	(8.87)	(12.84)	(9.38)	(1.19)	(1.13)
Number of investors (last round)	0.376***	0.376***	0.301***	0.301***	0.037***	0.037***
	(100.83)	(33.79)	(95.40)	(36.95)	(31.08)	(22.86)
Observations	71,613	71,613	71,613	71,613	71,613	71,613
R-squared	0.40	0.40	0.36	0.36	0.13	0.13
Fixed Effect	Ind + Year	Ind + Year	Ind + Year	Ind + Year	Ind + Year	Ind + Year
Cluster		Industry		Industry		Industry

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3: Survival Analysis Using CVC Exposure and Network Characteristics

This table repeats the test in Table 7 by replacing the *More Exposure to CVC* dummy with two dummies. *More CVC Exposure with Higher Centrality* is one if *More CVC Exposure* is one and maximum eigenvector centrality of the potential CVCs increases in the past 12 months. *More CVC Exposure with Lower or Same Centrality* is one if *More CVC Exposure* is one, and maximum eigenvector centrality of the potential CVCs does not increase in the past 12 months. *More M&A Activities* is a dummy that equals one if the number of all the M&As in the CBSA increases in the past 12 months. *log(Deal Value)* is the nature logarithm of deal value in millions USD. *log(Company age)* is the natural logarithm of number of years since the startup receives its first investment. *Round Number* is the round number in sequence of the transaction (if its the first round then *Round Number* is one; if its the seond round, then *Round Number* is two). All the regressions are stratified by startup industry, transaction year and outcome. Standard errors are clustered at the startup industry level.

	(1)		(2)		(3)	
	Marginal Effect	t-stat	Marginal Effect	t-stat	Marginal Effect	t-stat
More CVC Exposure with Higher Centrality						
Next Round	0.022***	(2.68)	0.021***	(2.65)	0.021***	(2.65)
Successful Exit	0.001	(0.04)	-0.001	(-0.04)	-0.001	(-0.05)
Failed Exit	-0.003	(-0.28)	-0.001	(-0.12)	-0.001	(-0.12)
More CVC Exposure with Lower Centrality						
Next Round	0.027***	(2.72)	0.025***	(2.62)	0.025***	(2.62)
Successful Exit	0.143***	(4.95)	0.138***	(4.97)	0.138***	(4.94)
Failed Exit	-0.007	(-0.58)	-0.003	(-0.28)	-0.003	(-0.28)
VCs Present						
Next Round			0.129***	(3.85)	0.130***	(3.67)
Successful Exit			0.266***	(5.56)	0.256***	(5.37)
Failed Exit			-0.087***	(-7.78)	-0.095***	(-8.13)
Buyout Investors Present						
Next Round					0.006	(0.20)
Successful Exit					-0.026	(-0.51)
Failed Exit					-0.031	(-1.28)
More M&A Activities						
Next Round	0.007	(0.86)	0.006	(0.83)	0.007	(0.82)
Successful Exit	0.030*	(1.89)	0.026	(1.56)	0.026	(1.54)
Failed Exit	-0.006	(-0.54)	-0.006	(-0.54)	-0.007	(-0.57)
log(Deal Value)	-0.123***	(-15.69)	-0.127***	(-16.72)	-0.127***	(-17.75)
log(Company age)	-0.435***	(-21.61)	-0.439***	(-22.47)	-0.439***	(-22.73)
Round number	0.045***	(11.30)	0.044***	(11.39)	0.044***	(11.31)
Observations	110,513		110,513		110,513	
Pseudo R-squared	0.0067		0.0069		0.0069	
Strata	Ind + Year + Outcome		Ind + Year + Outcome		Ind + Year + Outcome	
Cluster	Industry		Industry		Industry	

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A5: CVC Exposure and Network Characteristics of Current Round Investors

This table test the impact of CVC exposure on the network characteristics of current round investors. Dependent variable in column (1) is the average eigenvector centrality of investors in the current round. Dependent variable in column (2) is the maximum eigenvector centrality of investors in the current round. Dependent variable in column (3) is the average eigenvector centrality of new investors who have never invested in the startup in the past. Dependent variable in column (4) is the maximum eigenvector centrality of new investors who have never invested in the startup in the past. Independent variable *More CVC Exposure* is a dummy that equals one if the number of CVC parents doing M&A in the startup CBSA increases in the past 12 months. In Panel B, controls for the centrality of last round's investors are added. *Last round Ave* is the average eigenvector centrality of investors in the last round. *Last round Max* is the maximum eigenvector centrality of investors in the last round. *Last round New Ave* is the average eigenvector centrality of new investors in the last round. *Last round New Max* is the maximum eigenvector centrality of new investors in the last round. Industry and transaction year fixed effects are controlled. All the regressions are cluster by industry.

Panel A. Without Controls from Last Round

	(1) Current Ave	(2) Current Max	(3) Current New Ave	(4) Current New Max
More CVC Exposure	0.003***	0.003***	0.002***	0.002***
	(11.51)	(11.27)	(9.46)	(9.10)
More M&A Activities	0.001***	0.002***	0.002***	0.002***
	(4.60)	(6.55)	(5.84)	(7.92)
VCs present	0.016***	0.026***	0.014***	0.022***
	(19.17)	(22.11)	(16.36)	(21.21)
Buyout investors present	-0.008***	-0.002**	-0.009***	-0.004***
	(-11.34)	(-2.21)	(-11.73)	(-5.89)
log(Deal Value)	0.007***	0.015***	0.008***	0.012***
	(8.44)	(15.02)	(7.93)	(12.66)
log(Company age)	0.004***	0.006***	-0.004***	-0.007***
	(8.47)	(11.45)	(-6.44)	(-7.87)
Observations	111,040	111,040	72,270	72,270
R-squared	0.20	0.28	0.15	0.19
Fixed Effect	Ind + Year	Ind + Year	Ind + Year	Ind + Year
Cluster	Industry	Industry	Industry	Industry

Panel B. With Controls from Last Round

	(1) Average	(2) Maximum	(3) New Average	(4) New Maximum
More CVC Exposure	0.001***	0.001***	0.001*	0.001***
	(5.49)	(4.70)	(1.87)	(2.92)
More M&A Activities	0.000*	0.001***	0.002***	0.003***
	(1.70)	(3.11)	(4.36)	(5.39)
VCs present	0.008***	0.018***	0.010***	0.018***
	(19.78)	(21.65)	(11.21)	(14.31)
Buyout investors present	-0.004***	0.002***	-0.010***	-0.006***
	(-10.24)	(3.88)	(-13.01)	(-5.90)
log(Deal Value)	0.002***	0.009***	0.007***	0.012***
	(4.95)	(18.05)	(8.89)	(22.65)
log(Company age)	-0.000	-0.003***	-0.006***	-0.009***
	(-0.68)	(-6.64)	(-9.04)	(-11.29)
Last round Ave	0.642***			
	(61.33)			
Last round Max		0.625***		
		(63.54)		
Last round New Ave			0.140***	
			(15.72)	
Last round New Max				0.108***
				(11.60)
Observations	71,613	71,613	24,690	24,690
R-squared	0.58	0.61	0.16	0.20
Fixed Effect	Ind + Year	Ind + Year	Ind + Year	Ind + Year
Cluster	Industry	Industry	Industry	Industry

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A5: CVC Exposure and Network Characteristics of Current Round Investors

This table test the impact of CVC exposure on the network characteristics of current round investors. Dependent variable in column (1) is the average eigenvector centrality of investors in the current round. Dependent variable in column (2) is the maximum eigenvector centrality of investors in the current round. Dependent variable in column (3) is the average eigenvector centrality of new investors who have never invested in the startup in the past. Dependent variable in column (4) is the maximum eigenvector centrality of new investors who have never invested in the startup in the past. Independent variable *More CVC Exposure* is a dummy that equals one if the number of CVC parents doing M&A in the startup CBSA increases in the past 12 months. In Panel B, controls for the centrality of last round's investors are added. *Last round Ave* is the average eigenvector centrality of investors in the last round. *Last round Max* is the maximum eigenvector centrality of investors in the last round. *Last round New Ave* is the average eigenvector centrality of new investors in the last round. *Last round New Max* is the maximum eigenvector centrality of new investors in the last round. Industry and transaction year fixed effects are controlled. All the regressions are cluster by industry.

Panel A. Without Controls from Last Round

	(1) Current Ave	(2) Current Max	(3) Current New Ave	(4) Current New Max
More CVC Exposure	0.003***	0.003***	0.002***	0.002***
	(11.51)	(11.27)	(9.46)	(9.10)
More M&A Activities	0.001***	0.002***	0.002***	0.002***
	(4.60)	(6.55)	(5.84)	(7.92)
VCs present	0.016***	0.026***	0.014***	0.022***
	(19.17)	(22.11)	(16.36)	(21.21)
Buyout investors present	-0.008***	-0.002**	-0.009***	-0.004***
	(-11.34)	(-2.21)	(-11.73)	(-5.89)
log(Deal Value)	0.007***	0.015***	0.008***	0.012***
	(8.44)	(15.02)	(7.93)	(12.66)
log(Company age)	0.004***	0.006***	-0.004***	-0.007***
	(8.47)	(11.45)	(-6.44)	(-7.87)
Observations	111,040	111,040	72,270	72,270
R-squared	0.20	0.28	0.15	0.19
Fixed Effect	Ind + Year	Ind + Year	Ind + Year	Ind + Year
Cluster	Industry	Industry	Industry	Industry

Panel B. With Controls from Last Round

	(1) Average	(2) Maximum	(3) New Average	(4) New Maximum
More CVC Exposure	0.001***	0.001***	0.001*	0.001***
	(5.49)	(4.70)	(1.87)	(2.92)
More M&A Activities	0.000*	0.001***	0.002***	0.003***
	(1.70)	(3.11)	(4.36)	(5.39)
VCs present	0.008***	0.018***	0.010***	0.018***
	(19.78)	(21.65)	(11.21)	(14.31)
Buyout investors present	-0.004***	0.002***	-0.010***	-0.006***
	(-10.24)	(3.88)	(-13.01)	(-5.90)
log(Deal Value)	0.002***	0.009***	0.007***	0.012***
	(4.95)	(18.05)	(8.89)	(22.65)
log(Company age)	-0.000	-0.003***	-0.006***	-0.009***
	(-0.68)	(-6.64)	(-9.04)	(-11.29)
Last round Ave	0.642***			
	(61.33)			
Last round Max		0.625***		
		(63.54)		
Last round New Ave			0.140***	
			(15.72)	
Last round New Max				0.108***
				(11.60)
Observations	71,613	71,613	24,690	24,690
R-squared	0.58	0.61	0.16	0.20
Fixed Effect	Ind + Year	Ind + Year	Ind + Year	Ind + Year
Cluster	Industry	Industry	Industry	Industry

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A6: Cause-specific Survival Analysis with Exogenous Shock in Sub-sample

This table repeats the test in Table 7 in a sub-sample that excludes startups in two VEIC sectors, Computer Software and Internet Specific.

	(1) Marginal Effect	t-stat	(2) Marginal Effect	t-stat	(3) Marginal Effect	t-stat
More CVC Exposure						
Next Round	0.029**	(2.18)	0.027**	(2.02)	0.027**	(2.00)
Successful Exit	0.061	(1.41)	0.054	(1.25)	0.055	(1.28)
Failed Exit	-0.016	(-0.89)	-0.013	(-0.69)	-0.012	(-0.68)
VCs Present						
Next Round			0.157***	(3.03)	0.179***	(3.82)
Successful Exit			0.262**	(2.49)	0.304***	(3.07)
Failed Exit			-0.106***	(-5.94)	-0.124***	(-8.55)
Buyout Investors Present						
Next Round					0.072***	(2.99)
Successful Exit					0.088	(0.97)
Failed Exit					-0.056	(-1.50)
More M&A Exposure						
Next Round	0.020	(1.58)	0.018	(1.48)	0.019	(1.51)
Successful Exit	0.073*	(1.79)	0.068*	(1.67)	0.069*	(1.71)
Failed Exit	-0.014	(-0.76)	-0.015	(-0.81)	-0.015	(-0.83)
log(Deal Value)	-0.109***	(-8.45)	-0.113***	(-9.12)	-0.116***	(-9.31)
log(Company age)	-0.382***	(-14.67)	-0.389***	(-15.32)	-0.390***	(-15.34)
Round number	0.043***	(8.04)	0.043***	(8.18)	0.043***	(8.04)
Observations	57,871		57,871		57,871	
Pseudo R-squared	0.0068		0.0072		0.0073	
Strata	Ind + Year + Outcome		Ind + Year + Outcome		Ind + Year + Outcome	
Cluster	Industry		Industry		Industry	

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Biography

Hui (Susan) Zhou joined the Ph.D. program at the A.B. Freeman School of Business, Tulane University in 2017. Prior to pursuing doctoral studies, she earned a Master of Finance degree from Tulane University and a Bachelor of Economics degree from Zhejiang University.