Dancing with the Giants:
CVC Investments and Startup Outcomes

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ABSTRACT

This paper studies the strategic interactions between incumbents and startups by examining how Corporate Venture Capital (CVC) investments affect startup exit and innovation outcomes. Using an instrumental variable approach based on plausibly exogenous cash flow shocks from parent companies, I find that CVC involvement generally reduces the likelihood of startup failure and increases the chances of achieving an IPO rather than an acquisition. These findings indicate that incumbents, through CVC investments, likely provide valuable resources and strategic support. However, such benefits diminish–or even reverse–when CVCs exert excessive control by being dominant investors in a specific industry or by investing in early-stage startups, potentially stifling competition and raising anti-competitive concerns. Additionally, my analysis reveals consistent effects on startup innovation: CVC investments in early-stage startups reduce their disruptive innovations related to the CVC parent's market, while CVC investments in late-stage startups boost complementary innovations and innovations in CVC-unrelated areas. These nuanced outcomes highlight the need for entrepreneurs and regulators to carefully consider the implications of CVCs' influence on startups.

Keywords: Venture Capital, Corporate Venture Capital, Entrepreneurial Finance, IPO, Mergers & Acquisitions, Instrumental Variable

JEL Codes: G24

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1 Introduction

Incumbents and startups engage in interactions that can be both collaborative and competitive. On one hand, incumbents benefit from knowledge spillovers, strategic alliances, and patent licensing with startups. On the other hand, they also face competition from startups introducing disruptive innovations and posing entry threats in established markets. One unique way that allows large incumbent firms to interact with a wide range of startups is the *financing* channel through Corporate Venture Capital (CVC) investments.

This paper aims to investigate the strategic interactions between incumbents and startups by examining the impact of CVC investments on startup exit and innovation outcomes. Corporate Venture Capitals (CVCs) are in-house venture capital funds fully-sponsored by corporations to make minority equity investments in startups. What sets CVCs apart from traditional venture capital funds is their dual role. First, similar to traditional venture capital, CVCs seek *financial* return from their investments. Second, as the investment arm of a corporation, they also serve the *strategic* objectives of their parent company. These objectives may include knowledge transfer or creating synergies, but it could also include mitigating competition from startups.

CVC serves as a valuable context for studying the strategic interactions between incumbents and startups for several reasons. First, CVCs have become a prevalent force in the venture capital world. As of 2021, CVC-backed deals accounted for 20% of all venture-funded transactions, and 70% of Fortune 100 companies now have dedicated CVC units. Second, unlike other forms of corporate investments, such as majority acquisitions, CVCs provide a cost-effective way to realize strategic advantages. By making small minority stake investments, parent firms can gain influence and access to a startup's strategy, product development, and technologies without the need for full ownership, allowing them to leverage these benefits with a relatively modest financial commitment[1]. These unique characteris-

[1] For instance, in 2021, Alphabet Inc. (parent company of Google) reportedly completed four majority acquisitions, with the total amount reaching $2,618 million. In contrast, its CVC unit, Google Ventures, made 120 minority investments in startups, totaling only $1,822 million, with each deal averaging only $15

tics of CVCs have drawn increased scrutiny from regulators, who are concerned about the impact of CVC investments on competition. For instance, recently the U.S. Department of Justice (DOJ) has reportedly tightened enforcement of the "no interlocking directorates" rule, which prevents CVC representatives from sitting on the boards of competing companies.[2] However, there remain numerous, more nuanced channels through which CVCs can potentially influence startups beyond obtaining board seats.

The potential impact of CVC on startups is ambiguous. On the positive side, if startups receive essential funding from CVCs that they can't obtain elsewhere, or if they benefit from the unique support and resources offered by the CVC parent, they are more likely to achieve successful exits. Furthermore, within successful exits, one should expect CVC-invested startups to exhibit a higher likelihood of an IPO, which are generally more advantageous for investors and entrepreneurs than acquisitions (Bayar and Chemmanur, 2011), potentially also leading to higher competition in the product markets. On the negative side, if the CVC's primary motivation is to mitigate entry threats, CVC-invested startups may struggle to establish themselves as independent players against the incumbent CVC parent firm. This could result in both an increased likelihood of failure and a shift from IPO exits to acquisitions.

In this paper, I consider a sample of 1,941 CVC funds and a universe of 62,065 startups that secured startup financing rounds between 1982 and 2023. To address the selection issue—where CVC-selected startups may inherently differ from others—and to isolate the treatment effect of CVC investment, I employ an instrumental variables (IV) approach. Specifically, I exploit the institutional feature that CVC invests from its parent company's balance sheet, and thus the availability of funds is contingent on the parent's cash flow. I therefore use the segment-level cash flow shocks of the CVC parent that are *unrelated* to the startup industry as a plausibly exogenous variation in CVC funding and allocate these

million (assuming Google Venture contributes the same amount to each deal syndicate as other investors). The CVC investment total amount is equivalent to 7.4% of Alphabet's capital expenditure for the same period.

[2] see https://globalventuring.com/corporate/cvc-investments-face-increased-antitrust-scrutiny/

shocks to the startups within the industry based on their ex-ante exposure to CVC funding shocks.

The instrument's key identifying assumption is conceptually similar to a shift-share design framework, particularly one that assumes an exogenous shift while allowing for an endogenous share (Borusyak, Hull, and Jaravel, 2022). Empirical evidence supports this assumption (see Section 4.3 and 4.4 for a detailed discussion). While the unrelated cash flow may still correlate with the investment opportunities at the startup industry, a falsification test shows no link between the shock and total deal flow into the startup industry within the same year, supporting the shock's plausible exogeneity. Furthermore, variance analysis indicates that most of the instrument variation (83%) originates from the cash flow shock, with only 14% attributable to CVC-startup matching.

Using this instrumental variable approach, I examine the impact of CVC investments on startup exit outcomes. I find that receiving a CVC investment generally reduces the likelihood of startup failure at exit, increasing the chances of exit through IPO or acquisition. CVC investments could potentially benefit startups through two channels: providing additional source of funding, as well as offering resources and supports that are unique to CVCs but not to VCs. Further analysis shows that while funding is crucial for struggling firms on the edge of failure, the overall impact of CVCs extends beyond funding channel, with the support channel playing a greater role in enhancing IPO success.

In contrast, I also find CVC investments have anti-competition effects on the startup, particularly when CVC has a greater control over the startups. I explore two specific cases where this control is more pronounced. First, CVC investments in early-stage (pre-A Series) startups increase the likelihood of failure and reduce the likelihood of IPO exit. This is likely because early-stage CVC investors acquire larger shares of the firm and have a longer timeframe to influence the company's direction. Conversely, CVC investments in more mature stages are constrained by other investors, limiting the potential for CVCs to induce conflicts of interest. Second, the positive effects of CVC investment on IPO likelihood diminish if the CVC has greater dominance in investing in the startup industry, measured by the total number of deals invested by the CVC in a given industry over the previous five years. In such cases, startups are more likely to exit through acquisitions. Overall, the findings provide a nuanced view of CVC investments: while the effects of CVC are generally beneficial, entrepreneurs should be cautious if the CVC exerts significant control over the startup.

I further investigate a key channel through which anti-competitive effects of CVC investment manifest – by influencing startup innovation. This is particularly important because the notion of creative destruction relies on startups producing disruptive technologies that challenge incumbents' market power. Using the *RETech* measure from Bowen III, Frésard, and Hoberg (2022), which captures the extent to which a patent substitutes existing technologies, I classify startup patents as either disruptive or complementary to existing technologies. Additionally, based on a crosswalk between patent classes and industry classifications Goldschlag, Lybbert, and Zolas (2016), I attribute startup patents to those related or unrelated to the CVC's product market for each startup-CVC pair.

Using the IV specification, I find that early-stage startups reduce the production of disruptive innovations following CVC investments, but only in patent classes related to the CVC's product market. In contrast, late-stage CVC investments lead to a significant increase in innovation outputs in patent classes unrelated to the CVC's product market. Moreover, there is a slight increase in the number of complementary patents in CVC-related patent classes after late-stage CVC investments. These results suggest that CVC investments play a dual role in shaping startup innovation: curbing disruptive innovations that could threaten the CVC parent's core markets while fostering innovations in areas that are either unrelated or complementary to the incumbent's business.

The rest of the paper proceeds as follows. Section 2 discusses the literature. Section 3 describes the data and presents stylized facts about CVC investing. Section 4 presents the empirical strategy. Section 5 provides main results on startup exits and Section 6 provides results on startup innovation. Section 8 concludes.

2 Literature Review

This paper relates to literature that have analyzed (1) the impacts of CVC on parent company and invested startups, (2) conflicts of interest between financial investors and invested firms, and (3) the strategic behavior of the incumbent firms. In this section, I review these literature and discuss the contribution of the current study relative to them.

2.1 Impact of CVC investments

Prior studies have documented positive returns of CVC investments for the parent company. Gompers and Lerner (2000) show that the CVC investments yield financial returns comparable to those of average VC. Additionally, CVC provides avenues for learning and experimentation. CVC parent companies benefit from knowledge transfer acquired through invested ventures, thereby enhancing their innovation capacity (Dimitrova, 2015; Dushnitsky and Lenox, 2005; Kim, Gopal, and Hoberg, 2016; Ma, 2020). CVC also facilitates firms' expansion into new industries (Zhang, 2021), and aids in identifying acquisition opportunities (Benson and Ziedonis, 2010; Dyer, Kale, and Singh, 2004).

On the startup side, existing evidence suggests that there are positive effects of CVC investment on the startups, but the results are mixed. Startups backed by reputable CVCs tend to launch faster IPOs and obtain higher market valuations at IPO (Ivanov and Xie, 2010; Stuart, Hoang, and Hybels, 1999). Additionally, they receive higher acquisition premium as targets (Ivanov and Xie, 2010), particularly when there is strategic fit between the CVC and the startup. Post-IPO, CVC-backed startups are more innovative (Chemmanur, Loutskina, and Tian, 2014). However, research presents conflicting findings regarding exit outcomes: Kim and Park (2017) suggest that CVC investment reduces IPO likelihood but boosts innovation, while Liu (2024) argues that CVC investment increases both IPO likelihood and innovation. Most of these studies use a matched sample approach to address the CVC selection effects; one exception is Liu (2024), who employs a shift-share design to identify CVC flow at industry-year level. My study contributes to this strand of literature by introducing a more granular level instrument for CVC investments, which is necessary to study the strategic interactions between a specific CVC and a specific startup. This finer level of IV enables the revelation of significant anti-competitive effects of CVC by pinpointing precise scenarios where CVC may exert excessive control, which is new to the literature.

Relatedly, a theoretical strand of literature has explored the potential competitive dynamics between the startup and the CVC, evaluating how strategic motivations shape the CVC investment. Hellmann (2002) models the optimal financing choice between strategic investors (CVCs) and VCs in scenarios where differing degrees of strategic alignment exists between the startups and the CVC parent companies. Mathews (2006) proposes an alternative mechanism wherein CVC investment aligns interests between startups and CVC parent companies, particularly in contexts where potential competition arises between the two parties. Both studies predict a softened competition between the CVC parents and the startups, when their businesses are substitutive in nature. Despite these theoretical insights, the empirical evidence remains rare. This paper contributes to this literature by providing novel evidence that sheds light on the conditions where potential anti-competitive effects of CVC investments are more likely.

2.2 Conflicts of Interests between Financial Investors and Invested Firms

Several existing papers study the conflicts of interest between the VC and entrepreneurs regarding exit choices between acquisition and IPO, stemming from differences in private benefits or investment horizon differences (Bayar and Chemmanur, 2011; Ewens and Farre-Mensa, 2020), asymmetric cash flow rights (Cumming, 2008; Hellmann, 2006), or liquidity pressure toward the end of the investment period (Bhattacharya and Ince, 2012; Bian, Li, and Nigro, 2023; Masulis and Nahata, 2009). Moreover, VCs might transfer growth opportunities from one portfolio firm to other competing portfolio firms to maximize the portfolio returns, potentially at the expense of individual entrepreneurs' interests (Leccese, 2023; Li, Liu, and Taylor, 2023; Ueda, 2004). This paper augments the extensive literature by documenting a distinct source of conflict of interests arising from the strategic disparities between the CVC parent and the startups.

2.3 Strategic Behavior of Incumbent Firms

Finally, the paper contributes to a growing literature examining the strategic behavior of the incumbent firms. Kamepalli, Rajan, and Zingales (2020) theoretically establish how the possibility of incumbent firms creating kill zones around their product territory and quickly acquire any competing entrants leads concerned VCs to underinvest in such startups. Argente, Baslandze, Hanley, and Moreira (2020) empirically document that market leaders exhibit lower rates of product innovation but rely on patents to restrict competition. Akcigit and Goldschlag (2023) illustrate that incumbent firms strategically offer higher wages to inventors to dissuade them from implementing new ideas that could threaten their existing product market positions. In a more extreme scenario, Cunningham, Ederer, and Ma (2021) document how incumbents may acquire firms with competing products to eliminate rivals from the market. While acquisitions are commonly employed by incumbent firms to soften competition from firms with mature products or established product pipelines, this paper sheds light on how CVC can serve as a device for incumbents to engage with the startups at early stages. Specifically, it shows that although the overall effects of CVC investment are generally beneficial to startups, entrepreneurs and regulators should be more cautious when CVC invests in early-stage startups and when CVC has greater market dominance.

3 Data and Sample

3.1 Data Sources and Sample Construction

I obtain startup funding data from CB Insights. This data vendor provides information on the financing company, deal information including valuation, as well as the investor information. To construct the sample of startups, I select companies with at least one round of equity financing[3] of deal size greater than or equal to $1 Million USD, and the company's total funding exceeds $2 Million USD. I further obtain all the financing deals of the selected company. To be in the final sample, the startup should also have completed at least one startup equity financing deal in the sample period[4].

To identify corporate venture capital investors, I rely on the classification of CB Insights and select all investors whose investor type is labeled as "Corporate Venture". I also require that the investor to have completed at least one deal in the sample period. The final sample includes 62,065 startup companies which are included in 244,091 deals (with or without CVC investment), and 1,941 corporate venture capital funds, which in total invested in 34,676 deals.

I obtain the CVC parent company segment cash flow data from the Compustat Segment database, which contains the segment accounting information of US public firms. I manually match the CVC funds to its parent company in the Compustat Segment data, and obtain 1,009 CVC funds with matched GVKEY and 395 CVC funds with at least one segment cash flow data in the sample period. These funds represent 55.5% of the total capital invested in CVC.

To construct the startup-unrelated cash flow shock, one needs to link the industry classifications used in the Compustat Segment data (SIC, NAICS) and the CB Insight

[3]I define the deal as equity financing if the investment stage is in any of the follow categories: "Convertible Note", "Seed / Angel", "Series A", "Series B", "Series C", "Series D", "Series E+", "Other Venture Capital", "Private Equity", "Growth Equity".

[4]I define the deal as startup equity financing if the investment stage is in any of the following categories: "Angel", "Pre-Seed", "Seed", "Seed VC", "Series A", "Series B", "Series C", "Series D", "Series E+", "Venture Capital".

industries, the latter of which does not contain any unified industry classification other than a platform defined one. I manually created the link between the CB Insights industries and the SIC 4 digit code, based on the description of the SIC code and the corresponding Post-IPO SIC code of those that eventually went public. Because one only needs to exclude Compustat segments that are related to the focal startup industry, it is not necessary to create a one-on-one match between the two lists. Therefore, I adopt a conservative approach and select as many SIC industries that pertain to relate a focal CB Insights industry as possible.

3.2 Startup Exit Options

I obtain the exit outcomes of the startups from the history of startup deals. Specifically, I look for deals that attribute to an Acquisition (with Simplified Rounds belonging to either of “Acq- P2P”, “Acquisition”, “Acquisition (Financial)”, “Acquisition (Talent)”, “Merger”, or “Asset Sale”), IPO (“IPO” or “PIPE”) or Failure (“Bankrupt/Admin”, “Bankrupt/Liquidation”, “Dead”, “Distressed & Special Situation”, or “Dead”) event. In case that the firm experiences more than one exit events, I use the earliest exit event to label the exit outcome of the firm[5].

As Ewens and Farre-Mensa (2020) noted, CB Insights database is likely to under-report failure events, resulting in falsely positive active firm statuses. To capture additional failure exits, I match the sample with PitchBook data to collect additional information on company failure events and dates. Besides, some failures are misrepresented as acquisitions, with returns to investors and entrepreneurs being close to zero (“rescue acquisition”). I identify such acquisitions based on the firm valuation discounts at exit or, if exit valuations were missing, from the previous funding round. Furthermore, in case where none of the aforementioned failure events are identified, but CB Insight lists a company status as

[5] There are a number of firms with an IPO and an Acquisition exit on the same day (54 observations), which upon checking, all indicates reverse merger + PIPE. Therefore, I label them all as IPO instead of Acquisition.

"Bankrupt" or "Dead / Inactive", I also classify the company exit as failure. Companies not identified by these criteria are marked as "Active." Figure I presents the evolution of firm exit outcomes by the year of first funding.

I also gauge the CVC-startup specific exit information. Specifically, for each CVC-startup, if the startup exits in an acquisition, I can classify the identity of the acquirer with respect to the CVC. I label the startup acquisition exit as (1) whether the startup is acquired by CVC parent; (2) whether the startup is acquired by CVC competitors. Since the latter requires the acquirer to have a SIC code, which is not available for private firms, this measure will only be available to acquisition deals with public acquirers.

Table I Panel A presents the startup-level exit distribution. Active firms make up 30.24% of the sample, while another 40.99% have exited through an acquisition, 10.09% through IPO and 18.68% have failed. Panel B presents the startup exit outcomes by the last funding round before exit. As startups mature, the likelihood of an IPO increases from 3.03% at the Seed round to over 13.68% for Series D and even higher for later rounds. The likelihood of acquisition remains stable after Seed round and slightly decreases for D+ rounds, indicating a tendency for startups that stays private longer to choose IPO as eventual way of exits. Additionally, as startups raise more rounds of financing, the likelihood of failure rate decreases from 23.11% at Seed round to 17.5% at Series D round and even lower for D+ rounds.

Panel C presents the statistics of Acquirer Type at CVC-startup level. The table presents the CVC-startup pair, for all the startups regardless whether the startup was invested by the CVC (column "All startups"), and for startups that were invested by the CVC (column "CVC-invested startups"). The percentage is calculated as the number of CVC-startup pairs of which the acquirer is the focal CVC parent/CVC parent competitors over the total number of such CVC-startup pairs. It is noteworthy that the acquirer SIC code is obtained from Compustat, which is only available for US public firms. Therefore, the percentage of CVC parent competitors are calculated only within the CVC-startup pairs where the acquirer SIC code is non-missing.

3.3 Stylized Facts about CVC Investments

Figure II shows the annual startup equity financing deal volume of the firms in the sample, where the value represents the inflation-adjusted deal size in 2000 USD. The sample starts in year 1982 and ends in year 2023. There is a surge around year 2000 during the Internet Bubble, and there is an exponential growth of the startup financing deals in the most recent ten years. The red represents the volume of deals with at least one CVC investors. There is also a steady increase in the share of CVC-sponsored deals in the past ten years.

Table II characterizes the financing round distribution of CVC investments. The majority of the CVC investments are concentrated in Seed Round (15.98%), Series A (27.99%), Series B (23.27%), and Series C (13.53%), while the share of later rounds (Series D+) takes less than 10% each. However, the lower share of the later rounds of CVC could result from a smaller pool of eligible firms seeking such funding. Panel B shows the proportion of CVC-invested deals in proportion to the total number of deals for each individual financing rounds, and the CVC investment in Series D+ rounds constitutes around 15% - 25% of the total deal counts. Overall, CVC investment constitutes an important part of the startup funding across all stages of financing, although there are more deals in Seed and Series A to Series C rounds in absolute counts.

What leverage do CVCs have to influence startup outcomes? The answer may not be immediate apparent, especially considering that CVC typically acquires minority stakes in companies (Strebulaev and Wang, 2021). Nevertheless, three possible avenues exist through which CVC could impact startups. First, as outlined in Strebulaev and Wang's (2021) survey of CVC managers, the majority of respondents express a preference for obtaining either full board membership or board observer rights in the portfolio firms. These privileges empower CVC to exert influence and monitor the strategic movements of startups, enabling preemptive responses, including acquisition if the startup presents a viable threat to its product market. Second, approximately half of the surveyed CVC managers stipulate the requirement for a “Right of First Notice”, granting them priority notification in the event of takeover bids received by portfolio firms, allowing them to make counteroffers. Moreover, a notable 12% of respondents even require “Right of First Refusal”, providing them with veto power over any takeover bids directed at portfolio firms. Finally, a CVC can provide resources that complement the existing product positions of the CVC parent company. Entrepreneurs naturally find themselves better off by aligning their corporate strategy with these offerings, thereby reducing substitutability and enhancing complementarity to better leverage the assistance provided by CVC.

CVC also differs from other investors in terms of its investment style. First, CVCs are more likely to be the sole investors of a deal round. Panel A of Table III presents the regression results comparing CVC's probability of being the sole investor with that of other investors. Column (1) indicates that CVC are 6% more likely to be sole investors compared with an average investor, and when CVC invests in a follow-up deal of a round (for example, there could be multiple deals attributing to Series A financing, and the follow-up deals are not the first deal of the Series), it is 77.3% more likely to be the sole investor of the deal, compared against other follow-up deals.

In addition, CVC seems to be willing to pay for a higher valuation than average investors. Column (1) of Panel B shows that CVCs are more likely to pay higher valuation when it is the sole investor of the deal, and comparing across firms within the same investment stage, CVCs tend to pay 13.4% more in valuation compared with other investors. Nonetheless, this result could be purely driven by the fact that CVC tend to select higher valuation targets to invest. In Column (2), when a more stringent firm-round fixed effects are included, the CVC's paid valuation is compared with other deals within the same firm and the same series, which alleviates any concern for firm quality difference. CVC is still shown to pay a 4.91% higher valuation when it is the sole investor in a deal.

Why does CVC strive to be single round investors and accept higher valuations? To begin with, entrepreneurs may anticipate potential conflicts of interest arising from the strategic motives of CVC, leading them to demand higher compensation initially. Additionally, as Strebulaev and Wang (2021) shows, CVC often seek additional contractual rights in exchange for their investment, increasing the overall cost compared to typical investors. Thus, by being the sole investor, CVCs gain more freedom to negotiate such rights and potentially more flexible valuations. Moreover, contractual rights acquired in a deal are shared among all investors, necessitating majority consent for their exercise, such as Rights of First Refusal. Therefore, for CVCs to exert significant influence over startups, it is crucial that they become single-round investors.

4 Empirical Methodology

This section outlines the identification strategy, employing the instrumental variable (IV) approach to estimate the causal impact of CVC investments on startup outcomes. Section 4.1 defines the instrumental variable, while Section 4.2 explains the key identifying assumptions underlying the IV approach. Finally, Section 4.3 presents tests on the validity of the IV and Section 4.4 addresses potential concerns regarding violations of the IV exclusion restriction.

4.1 Instrumental Variable

Suppose that a startup's outcome is generated by the following model:

$$y_{ijt} = \delta D_{ijt} + \beta' X_{ijt} + \epsilon_{ijt} \tag{1}$$

for startup i, CVC j, and year t. The varaible y_{ijt} is the startup's outcome, D_{ijt} is an indicator variable with value of one if the startup i receives investment from CVC j in year t (and zero otherwise), and X_{ijt} is a vector of other observable characteristics of the startup i, CVC j, or the joint characteristics between i and j, in year t. The error term

ϵ_{ijt} represents the part of the startup's outcome unexplained by these variables. Under this model, the coefficients δ are the causal effects of a CVC investment into startup i's outcome after the investment.

OLS estimates of equation (1) would likely lead to biased and inconsistent estimates, because a CVC's investment decision into a startup (D_{ijt}) is likely to be correlated with the startup's outcome due to its unobserved characteristics (ϵ_{ijt}). For this reason, I instrument the CVC investment decision variable D_{ijt} with the following instrumental variable: the expected amount of funding available to a CVC to invest in a particular startup. Specifically, it is defined as

$$IV_{ijst} \equiv CF_{jt}^{-s} \times \mathbb{E}_{t-1} D_{ijt} \tag{2}$$

for all startups i, CVCs j, startup industry s, and years t. The variable CF_{jt}^{-s} denotes the cash flow shock to the CVC's parent firm that is unrelated to the industry of startup i, and $\mathbb{E}_{t-1} D_{ijt}$ denotes the focal CVC j's ex ante investment probability to invest in the startup i in year t estimated using information on or before year $t-1$.

The use of CVC parent firm cash flow shock (CF_{jt}^{-s}) as the first part of the IV is driven by an institutional feature of CVC. Unlike traditional VCs which start with a fundraising cycle and invest out of the committed capital of Limited Partners, most CVCs invest from the parent company's balance sheet (Strebulaev and Wang, 2021); as a result, the funding available for CVC investment is highly sensitive to the cash flow of the parent company. While the total cash flow of the parent company is correlated with the amount of funding available for CVC investment, it is not exogenous to the outcome of the CVC-invested startups because the cash flow of the parent company might be correlated with the investment opportunity of the startups if they are from the same industry. I construct my instrument using the segment cash flow of the CVC parent company that are unrelated to the investment opportunities of the startup's industry.

The unrelated segment cash flow from the focal startup's industry is constructed in two steps. First, I establish a crosswalk between the industry classification of the startup sample and the 4-digit SIC codes from the Compustat Segment database. This allows for the exclusion of Compustat segments of the CVC parent company that overlap with the startup's industry. Second, although the cash flows excludes the focal startup industry, there might still be common productivity or demand shocks between the focal industry and other industries. Therefore, to further eliminate correlations in investment opportunitie caused by these common shocks, I orthogonalize the resulting cash flow from the total annual cash flow of the startup's industry. This is achieved by conducting a 10-year rolling window regression at the CVC-industry level and extracting the residual term. This approach also helps mitigate concerns that overly aggregated segment reporting (as noted by Hoberg and Phillips (2022)) may attribute unreported focal industry cash flows to other closely related reported industries, thereby preserving the exogeneity of the cash flow.

While the cash flow shock creates an exogenous variation for a CVC-industry-year, in the second step the cash flow shock is assigned to individual firms within the industry depending on their pre-determined exposure to the CVC cash flow, which is estimated as the CVC-startup ex ante investment probability, reflecting the likelihood of a startup receiving CVC funding based on its characteristics. Specifically, for a CVC j in year t, the ex ante probability of it investing in a startup i is calculated in the following steps. First, for every CVC j – year t, I estimate the following probability regression using startup's characteristics to predict next period probability that the CVC investing in the startup, using the CVC's historical investment on or before $t-2$:

$$D_{ij(\tau+1)} = \beta' X_\tau + \epsilon_{ij(\tau+1)}, \quad \text{where } \tau \leq t-2 \tag{3}$$

X_τ represents a battery of startup characteristics as of year τ, including patent stock, past 3 year patent growth and patent citation growth, indicators of financing stage (Pre-A/Round A-C/Post-C/Other), business description similarity with CVC's past invested firms (median and maximum similarity with firms of past 3 year deals and all past deals, respectively), inflation-adjusted total funding raised in the past 1/2/3 years, number of active firms in the focal industry for the current year, number of years since founded, and indicators for industry. I denote the β estimated from Equation (3) as $\widehat{\beta_{\leq t-2}}$ as it is estimated using historical data on or before $t-2$.

Next, I define the ex ante probability of CVC investment in startup of year t using the startup's characteristics from $t-1$ and the estimated regression coefficients from $t-2$:

$$\mathbb{E}_{t-1}D_{ijt} \equiv \widehat{\beta_{\leq t-2}}' X_{t-1} \tag{4}$$

The specification using historical CVC investment records ensures that there is no forward-looking bias when calculating the instrument, as everything is determined one year before the focal year t. The ex ante investment probability $\mathbb{E}_{t-1}D_{ijt}$ reflects the historical pattern of CVC investment, and is a reduced-form way to estimate a matching probability between the CVC and the startup, reflecting both how the startup fits the profile of likely CVC investees, and how the startup is likely to accept the CVC's funding.

Finally, the instrument is calculated by taking the product of the unrelated cash flow generated in step one and the ex ante predicted likelihood of CVC investment generated in step two. Since both parts represent continuous degrees of change, I normalize both variables by adding a positive constant to all observations, ensuring that both parts are non-negative. This normalization prevents discontinuities around zero that could result from a sign flip.

Table IV presents the first stage of the instrumental variable regression. When regressing the endogenous CVC investment likelihood, 1(CVC-startup), on the IV, I find a statistically significant and positive coefficient, supporting the relevance condition. In particular, a one-standard-deviation increase in the IV is associated with a 31.9% increase in the CVC investment likelihood, relative to the sample mean. The Kleibergen-Paap F-stat is 29.3, exceeding the weak instrument test threshold of 10, as recommended by (Stock and Yogo, 2002). The positive coefficient on the IV suggests that a startup has a higher probability of receiving the investment from a particular CVC in a given year if it is exposed to a larger unrelated cash flow shock from the CVC parent company.

The instrument introduces an exogenous shock to the CVC funding available to the startup, akin to a quasi-natural experiment where the CVC's ability to invest is exogenously constrained, compelling the startups to accept the alternatives to receiving CVC funding. These alternatives could be in either of the two scenarios: either the startup receives alternative source of funding (for example, from a VC) or the startup receives no funding at all. The treatment effects of CVC, as estimated by the instrumental variable (IV), represent an average of the impacts from both scenarios.

4.2 IV Identifying Assumption

The instrument shares similarities with a shift-share design (Adao, Kolesár, and Morales, 2019; Autor, Dorn, and Hanson, 2013; Borusyak and Hull, 2023; Borusyak et al., 2022; Goldsmith-Pinkham, Sorkin, and Swift, 2020), where the instrument is defined as the sum of products between multiple industry-level shocks (the "shift") and location-specific weights (the "share") capturing the location's specific exposure to the shock. In this study, the instrument is a special form of the shift-share design, with a single shock originating from the CVC-industry-year level relevant to the startup's affiliation industry. Two main strands of literature provide framework for establishing the validity of shift-share IVs based on different identifying assumptions. Goldsmith-Pinkham et al. (2020) establish the validity of the instrument through the exogeneity of the shares, while Borusyak et al. (2022) derive identifications from the quasi-random assignment of shocks, allowing for the shares to be endogenous. The identifying assumption in this study follows the framework of Borusyak et al. (2022). In the remainder of this section, I outline how this framework is applied to the specific case of this IV, which involves a single shock.

Let y_l denotes the outcome of startup l. Let x_l be a dummy variable denoting whether the startup l receive a particular CVC investment. Let w_l be control vector. We start with the structural model of y

$$y_l = \alpha + \beta x_l + w_l'\gamma + \epsilon_l \tag{5}$$

The coefficient β is interpreted as the causal effect of x_l. Note x_l may be arbitrarily correlated with ϵ_l. For example, CVCs tend to choose startups that are more likely to have an IPO exit, so when y is the likelihood of an IPO exit, ϵ_l is positively correlated with x_l, reflecting the endogeneity of x if directly estimating equation (5) in OLS. Consider a candidate instrument defined as below

$$z_l \equiv s_{ln} \times g_n \tag{6}$$

where the g_n denotes the cash flow shock at CVC-industry-year n level, while s_{ln} denotes the startup l's exposure to the CVC-industry-year shock n. By the Frisch-Waugh-Lovell theorem (Frisch and Waugh, 1933; Lovell, 1963), β could be estimated in an IV regression of y_l, with x_l instrumented by z_l and controlled for w_l The identifying condition of β by the full-data moment condition is given by

$$\mathbb{E}[z_l \epsilon_l] = 0 \tag{7}$$

This condition captures the orthogonality of the instrument with the second stage residual.

Assumption 1 *(Quasi-random shock assignment)*: $\mathbb{E}[g_n \epsilon_l | s_{ln}] = 0$, for all l.

Assumption 1 captures the notion of the shock part g_n beging “as-good-as-randomly-assigned” (Borusyak et al., 2022) with respect to the residual term conditional on the shares. This corresponds to the identifying assumption that the exogeneity comes from the shock part of the shift-share IV.

Proposition 1 The identifying condition of the shift-share IV (7) is met if Assumption 1 holds.

Proof: by Assumption 1 and the law of iterated expections,

$$\mathbb{E}[z_l \epsilon_l] = \mathbb{E}[g_n s_{ln} \epsilon_l] = \mathbb{E}[\mathbb{E}[g_n s_{ln} \epsilon_l | s_{ln}]] = \mathbb{E}[s_{ln} \mathbb{E}[g_n \epsilon_l | s_{ln}]] = \mathbb{E}[s_{ln} \cdot 0] = 0$$

Therefore, the proposed instrument z_l is a valid instrument for estimating the causal effect captured by β, in that IV identifying moment condition equation (7) holds.

4.3 IV Validity Tests

In this section, I provide evidence on the validity of the instrument. First, I demonstrate the plausible exogeneity of the cash flow shock through a falsification test. Second, I break down the black box of the shift-share instrument by analyzing the contributions of its various components to the overall variations of the instrument. Finally, I discuss two robustness tests that address concerns of endogenous CVC-startup matching driving the results.

First, I demonstrate the plausible exogeneity of the shock using a falsification test. Following Borusyak et al. (2022), I employ a regression-based approach to test shock orthogonality by regressing an observed proxy for the unobserved residuals on the shock component of the instrument. In this context, the proxy should reflect the investment opportunities of startups, which correlate with their exit outcomes. I use the industry-level total deal flow from all investors as the proxy. Table B.1 shows that CVC-industry-level unrelated cash flow does not predict startup-industry deal flows. Column (1) indicates that a 1% increase in unrelated cash flow corresponds to only a 0.0019% increase in industry-year deal flow from the mean. In Column (2), after including additional year fixed effects, the correlation becomes insignificantly negative, resulting in a 0.0068% decrease from the mean. Overall, these results provide evidence consistent with exogeneity of unrelated cash flow as the shock component of the instrument.

Second, I investigate the sources of variations in the instrument. While most variation is expected to stem from the exogenous shock component, a concern is that a permanent

CVC-startup matching component could overshadow the cash flow shock, making it appear as only a small perturbation. To address this concern, I first conduct a mixed effects Analysis of Variance (ANOVA) test to examine the variability attributed to the shock (at the CVC-industry-year level) versus the matching (at the CVC-startup level). The results reveal that the shock accounts for 83.27% of the total variance, while the matching explains 13.77%, and the unexplained residuals constitute the remaining 2.96%. Next I employ an alternative approach by calculating the partial R^2 for the fixed effects representing the shock (CVC-industry-year FE) and the matching (CVC-startup FE). The results indicate that the shock fixed effects contribute an additional 83.33% of explanatory power, whereas the matching fixed effects contribute only 12.82% of explanatory power[6]. Overall, these results suggest that the majority of the variation in the instrument is driven by the shock component.

Third, to further address concerns that the endogenous share component associated with CVC-startup matching drives the result, I conduct two robustness tests. In the first sets of tests, I apply the "recentering treatment" method proposed by Borusyak and Hull (2023). This technique corrects biases arising from different observations receiving systematically different treatments because of their individual nonrandom "exposure" to the exogenous shock. The main concept is to calculate an "expected" instrument based on permuted shocks and original exposure, and then generate the "recentered" instrument by subtracting the realized instrument from the expected one. In the second set of tests, I restrict the analysis to subsamples of startups with high ex ante predicted probabilities. If the results are primarily driven by variations in endogenous ex ante predicted probabilities, we would not expect the instrument to yield significant results within these subsamples, where the predicted probabilities are tightely restricted and the majority of the variation arises from the shock component. Section 7 discusses the robustness of the results obtained through

[6]The regression with only CVC-industry-year FE yields an adjusted-R^2 of 0.78, while the regression with only CVC-startup FE yields an adjusted-R^2 of 0.48. Including both sets of FEs results in an adjusted-R^2 of 0.88. Thus, the partial R^2 of the shock component (CVC-industry-year FE) is (0.88-0.48)/0.48 = 83.33% while the partial R^2 of the matching component (CVC-startup) is (0.88-0.78)/0.78 = 12.82%.

these two approaches.

4.4 Discussions of Potential Violations of the Exclusion Restriction

This section addresses concerns regarding potential violations of the identifying assumptions outlined in Section 4.2.

4.4.1 Cash Flow Shock Creating a Selection on the Startup Quality

It is possible that CVCs follow a pecking order in selecting startups based on quality in response to varying cash flow shocks. One might be concerned that it may induce a selection bias in startup quality and undermine the exogeneity of the instrument. To address this concern, we can revisit a simplified version of the first stage

$$\mathbb{1}(CVC\text{-}startup)_i = \alpha + \beta z_i + w_i'\gamma + u_i \tag{8}$$

where $\mathbb{1}(CVC\text{-}startup)_i$ is the endogenous dummy variable indicating CVC investment in a particular startup, and z_i is the instrument while w_i denotes a vector of all other controls. β represents the overall variation in the likelihood of CVC investment induced by the instrument, and the residual term u_i accounts for firm-specific characteristics affecting the realized likelihood of CVC investment that are not captured by the instrument or the controls. Notably, the perceived quality of the startup, which may influence CVC's investment pecking order, could enter through u_i. For example, if a high-quality startup receives CVC investments despite a negative cash flow shock, it would be associated with a high u_i that is independent of the instrument variation and positively correlated with startup quality. However, this does not invalidate the instrument, as the second stage does not utilize the endogenous *realized* CVC investment. Instead, we only use the *predicted* CVC investment induced by the instrument, thereby excluding the effects of u_i.

4.4.2 Cash Flow Shock Directly Affecting Startup Outcomes

The exclusion restriction requires that the instrument should not have a direct effect on the outcome variable other than through affecting the instrumented variable. However, there are concerns that the cash flow shock may be directly linked to the CVC's interactions with the startup. For instance, when a CVC parent experiences a negative cash flow, it may face constraints on the resources and support it can provide to the startup. Conversely, a negative cash flow might also lead the CVC to compete less aggressively in the product market with the startup, thereby reducing anti-competitive effects.

Ideally, cash flow shocks should induce only perturbations in the CVC parent's short-term performance without affecting its long-term fundamental value. If these shocks are persistent or exhibit trends, it could pose problem. To assess the nature of these cash flow shocks, I model them using an AR(1) process and find a low autocorrelation coefficient of 0.18, indicating that the cash flow process is relatively stationary and will tend to mean-revert over time. Notably, on average, it takes a startup 8.6 years to exit, suggesting that any short-term variations from cash flow shocks are likely to subside by the time the startup's exit outcome is realized.

To further assess the transient nature of the cash flow shock, I examine its relationship with the CVC parent's next 5-year average fundamentals. If the cash flow shock has a lasting impact on the CVC parent's long-term performance and competitiveness, it should be positively correlated with the future 5-year firm fundamentals. Table B.2 presents the estimates. All equations include CVC fixed effects to ensure that comparisons are made within the same CVC parent company across different years, and the standard errors are clustered at the CVC level to account for within-CVC correlations, particularly because the dependent variables are slow-moving 5-year rolling window averages. The results indicate that there is no significant correlation between the cash flow shock and the CVC firm's next 5-year average firm fundamentals, as evidenced by both high p-values and low within R^2. The small standard errors suggest that these null results are not due to measurement noise or insufficient statistical power.

4.4.3 Independence of Shift and Share

A potential violation of the identifying assumption is that the cash flow shock is not independent of the ex ante predicted probability. For instance, if CVCs allocate more funding to startups of certain characteristics following a positive cash flow shock, this could create a systematic correlation between the shift and the share. While the instrument in this study uses an ex ante predicted probability estimated based on CVC's historical investment patterns – mitigating concerns about shares responding to contemporaneous cash flow shock – nonetheless, it would remain problematic if the ex ante predicted probability reflects the influence of by past cash flow shocks that may correlate with concurrent cash flow shocks. Although this is unlikely due to the transient nature of the cash flow shocks, as discussed in Section 4.4.2, I conduct an OLS regression of the ex ante predicted probability directly on the shock, using the same specification as the first stage of the baseline regression. Table B.3 presents the regression results. I find a small and insignificnat coefficient for the ex ante predicted probability (14.2 for a Y mean of 4985.4), with a minimal within-R^2 of 0.0006.

5 Effects of CVC Investments on Startup Exits

5.1 Baseline Regression Results

In this section, I estimate the impact of CVC investment on startup exit options using various estimation methods. The sample consists of a CVC-startup-year panel which is constructed as follows. For each CVC-subindustry in which the CVC investments are made, I obtain the dates of its initial and final startup equity financing deals, thereby generate a panel of CVC-subindustry-year spanning all the years between the first and last deal date. Next, I include all the startups from the subindustry that are active in the focal year.[7] The

[7] A startup is considered active from its start year, defined as the year of its initial equity financing deal, until the end year. The end year is determined by either its exit deal (IPO, bankruptcy, or acquisition) or,

sample includes firms with at least ten years observations after the first funding deals to observe firm exits.[8] I estimate the following Two-Stage Least Square (2SLS) regressions:

$$(1^{st}\text{ Stage}) \qquad \mathbb{1}(CVC\text{-}startup)_{ijst} = \beta_0 IV_{ijt} + \beta_1' X_{it} + \alpha_{st} + u_{isjt} \tag{9}$$

$$(2^{nd}\text{ Stage}) \qquad Y_{ijst} = \beta_2 \mathbb{1}(\widehat{CVC\text{-}startup})_{isjt} + \beta_3' X_{it} + \gamma_{st} + \epsilon_{ijst} \tag{10}$$

where i denotes startup, j denotes CVC, s denotes startup industry, and t denotes year. The dependent variables, denoted as Y_{isjt}, are a set of dummy variables indicating specific outcomes for a startup, including IPO, failure, acquisition, or acquisition by the CVC parent. The vector X_{it} captures a range of time-varying control variables, such as startup age, as well as controls from year t-2, including patent stock, patent citations and growth rates, funding size over the past 1, 2, and 3 years, and the number of peer startups within the focal industry. Both first and second stages also include startup industry-year fixed effects (denoted as α_{st} and γ_{st}). The standard errors are double clustered at the startup industry level and CVC-industry-year level.

The baseline estimates are presented in Table V. Column (1) of each table presents the OLS regression results where the dependent variable, the exit option dummies, are regressed directly on the endogenous variable $\mathbb{1}(CVC\text{-}startup)$, which take the value of one if the CVC invests in the focal startup in the current year. Column (2) and (3) presents the Two-stage least square (2SLS) IV estimates. Column (2) presents the first-stage results where the endogenous variable $\mathbb{1}(CVC\text{-}startup)$ is regressed on the instrumental variable, while Column (3) presents the second-stage results where the dependent variable, the exit outcome dummies, are regressed on the instrumented endogenous variable $\mathbb{1}(CVC\text{-}startup)$. Each stages is estimated in a linear probability model. In Column (4), the dependent variable is directly regressed on the instrument in a linear probability model.

if its record becomes stale, up to 5 years after its last equity financing deal with startups.

[8] The median exit time for startups is 8 years; thus, I chose a 10-year cutoff to ensure the representativeness of the exit outcome sample and to avoid truncation bias. Robustness tests in Table B.7 show that the results are unchanged if using five years as sample cutoff.

Panel A presents the effects of CVC investment on the probability of the startup having an IPO exit. Column (1) shows the OLS regression results. The positive coefficients indicate that CVC-invested startups show a significantly higher likelihood of IPO exit compared with non-CVC-invested startups. Column (2) to (4) of Panel A presents the results of IV regressions. Column (2) of Panel A shows that the IV strongly predicts the probability of CVC investment in the startup. In Column (3), the instrumented probability of CVC investment is estimated to have a statistically significant positive effect on the likelihood of IPO exit. The implied economic magnitude is substantial: a 1 percentage point exogenous increase in the CVC likelihood of investment leads to a 2.87 percentage point increase in startup IPO likelihood. To put it into perspective, 1% increase in CVC likelihood from the current mean is associated with 0.11% increase of IPO likelihood, also evaluated at the mean[9]. The results from the reduced form IV estimation in Column (4) is consistent with the effects in Column (3): the increase in IV is strongly correlated with the increase in the IPO likelihood.

Panel B presents estimates of the effects of CVC investment on the startup's probability of failure exit. Column (1) shows that CVC-invested startups are significantly less likely than non-CVC-invested startups to have a failed exit. The IV estimates in Column (3) and (4) shows that receiving CVC investment leads to a statistically significant reduction in the likelihood of a failed exit: for a 1 percentage point exogenous increase in the CVC likelihood of investment, the startup's failure rate decreases by 1.73 percentage point, which is equivalent to a 0.04% reduction in failure likelihood from the mean for a 1% increase in CVC investment likelihood from the mean.

Panel C demonstrates the effects of CVC investment on a startup's probability of an acquisition exit. Column (1) shows that, on average, CVC-invested startups are significantly more likely to experience an acquisition exit than an average non-CVC-invested startups. However, the IV regression indicates that receiving CVC investment is only associated with a

[9] In the current panel data, the mean likelihood of IPO likelihood is 0.14 and mean of 1(CVC-startup) is 0.006. Therefore, the economic magnitude for 1% increase in the CVC likelihood from the current mean evaluated at the mean of IPO likelihood is calculated as: 2.87% $\times$ 0.006/ 0.14 = 0.11%.

marginally significant reduction in the acquisition likelihood. Nonetheless, this IV estimate reflects an average change in the acquisition exit likelihood for startups at different funding stages. As Section 5.3 will show, there is a heterogeneous response in this likelihood across different stages.

Panel D presents the estimates of the effects of CVC investment on a startup's probability of exiting through an acquisition by the focal CVC's parent company. Column (1) indicates that CVC-invested startups are more likely to be acquired by the CVC parent compared to non-CVC-invested startups. Notably, the panel includes all CVC-startup pairs encompassing the universe of active startups, regardless of whether the focal CVC actually invests in them. It is also possible for a startup to be acquired by the CVC parent company even if it did not initially receive CVC investment. Therefore, we can estimate the likelihood of non-CVC-invested startups being acquired by the CVC parent. The IV results in Columns (3) and (4) show that a 1 percentage point exogenous increase in the likelihood of receiving CVC investment results in a 0.44 percentage point increase in the likelihood of a startup being acquired by the CVC parent company, with the effects being statistically significant. Economically, this corresponds to a 1.76% increase in the likelihood of acquisition by the CVC parent, evaluated at the mean, for a 1% increase in the likelihood of CVC investment from the mean.

Overall, the results in this section are consistent with positive effects of CVC investments on the startup outcomes. On average, the CVC-invested startups become less likely to fail and more likely to experience successful exits through either IPOs or acquisitions by the CVC parent company. However, the effects of CVC investment could potentially differ by the stages of startups or the dominance of CVC, due to variations in the duration of influence and the degree of CVC's control over the startup. Therefore, in the Section 5.3 and 5.4, I explore the heterogeneous effects of CVC investments along these dimensions.

5.2 Just Funding or CVC Funding In Particular?

CVC investments could benefit a startup in two main ways. First, a CVC can provide funding for the startups ("funding channel"). When CVC funding and traditional VC funding are not perfectly substitutes, CVC investment can fill a funding gap and enhance a startup's growth prospect. Second, CVC offers unique support and resources beyond what traditional VCs can provide ("support channel"). This benefit persists even for the startups that are already well-funded.

These two channels are likely to impact different types of startups. For startups on the margin of failure or survival, the funding channel may be more critical, as these firms also struggle with insufficient funding. In contrast, for higher-quality startups with competitive funding supplies, the support channel may play a more significant role. In such cases, the support channel is expected to influence outcomes related to IPOs rather than risk of failure.

To differentiate the effects of the two channels, I modify the 2SLS regression from Section 5.1 by adding an additional control variable for the total funding amount raised by the focal startup in the focal year. This variable captures the impact of the funding channel, while any remaining effects after controlling for funding size can be attributed to the support channel.

Table VI presents the second-stage estimates of the 2SLS regression. The coefficients across all columns decrease in magnitude, suggesting that both the funding and support channels influence startup outcomes. Notably, the effect on the failure rate becomes insignificant after controlling for funding size, while the effect on IPO likelihood remains significant. This aligns with the differing importance of the two channels: CVC investment helps certain firms by providing additional funding that lowers their failure rate, but its overall impact extends beyond financial support. CVC investment offers unique resources and support that cannot be replaced by traditional VC funding, thereby increasing the likelihood of an IPO.

5.3 Exit by Different Investment Stages

The influence CVC can exert on a startup varies depending on the stage at which the investment is made. An early investment could be associated with a larger stake, and in the meantime providing the CVC with more time to shape the direction of the startup's business and product market plan during its formative stages. Therefore, in this section, I investigate the heterogeneous treatment effects of CVC investment across various stages of startup funding.

I estimate the 2SLS IV regression by interacting the CVC investments with indicators of different startup funding stages. Specifically, I estimate the following regression:

$$
\begin{aligned}
(1^{st}\text{ Stage})\quad & \mathbb{1}(CVC\text{-}startup)_{ijst} \times \mathbb{1}(Stage)^k_{it} \\
& = \sum_k IV_{ijst} \times \mathbb{1}(Stage)^k_{it} + \mathbb{1}(Stage)^k_{it} + \beta_0' X_{it} + \alpha_{st} + u_{ijst} \qquad (11) \\
(2^{nd}\text{ Stage})\quad & Y_{ijst} \\
& = \sum_k \gamma^k \left[\widehat{\mathbb{1}(CVC\text{-}startup)_{ijst}} \times \mathbb{1}(Stage)^k_{it} \right] + \beta_1' X_{it} + \gamma_{st} + \epsilon_{ijst} \qquad (12)
\end{aligned}
$$

where k denotes various investment stages of the startup funding: Seed/Angel, A-C Rounds, D+ Rounds, respectively. This specification effectively captures the heterogeneous effects of receiving CVC investments during different stages of the startup on the exiting outcomes.

Table VII presents the IV regression results. Two observations of the results are in place. The impact of CVC investments on late stage startups (Post-C Rounds) appears to be similar to that of the baseline results. The coefficients of $\mathbb{1}(CVC\text{-}startup) \times \mathbb{1}(Post\text{-}C\ Rounds)$ of Column (1) is -1.22, although it is statistically insignificant at the 10% level. The coefficients from Column (2) to (4) also exhibit a similar pattern with the baseline: for 1 percentage point increase in CVC investment likelihood, startups are 11.5% more likely to have an IPO exit and 10.3% less likely to have an acquisition exit. This result indicates a shift of exit probability from acquisition to IPO, conditional on a successful exit. In the meantime, consistent with the baseline regression result, receiving CVC investment also increases the likelihood of acquisition exits by CVC parent.

However, the effects of CVC investments on early stage startups exhibit contrasting results from the late stage counterparts. The coefficient of $\mathbb{1}(\mathit{CVC\text{-}startup}) \times \mathbb{1}(\mathit{Pre\text{-}A\,Rounds})$ of Column (1) indicates that when invested by CVC in Pre-A rounds, the startups are significantly more likely to fail (1 percentage point increase in the CVC likelihood increases the failure rate by 10.8%). Among startups that achieve a successful exit, the likelihood of an IPO decreases by a substantial 10.9% for one percentage point increase in CVC investment likelihood, which is statistically significant at the 1% level. Additionally, there is a 0.1% increase in the likelihood of an acquisition exit, though this effect is statistically insignificant at the 10% level. It's noteworthy that include controls for the startup life cycle (e.g., startup age) and other lagged firm characteristics. Therefore, the observed differences between early-stage and late-stage investments are not attributable to variations in firm quality at the time of receiving these investments. Overall, these findings suggest that CVC investment in early stages increases the risk of failure for startups. Furthermore, among those that do exit successfully, there is a notable shift from IPOs to acquisitions, implying that such startups may face greater challenges in establishing themselves as independent competitors in the product market.

The shift from IPO exits to acquisition exits could be explained by two potential mechanisms: synergy and anti-competition. If a CVC provides complementary resources and realigns the startup's business with the CVC parent's, thereby creating synergistic value, the startup becomes a more attractive acquisition target for the CVC parent company compared to remaining a stand-alone public company. This would increase he likelihood of an acquisition exit. On the contrary, if CVC investments diminish the startup's growth potential and limit its ability to become an independent market competitor, a similar shift form IPO to acquisition exits would also be observed. However, these two mechanisms offer different predictions regarding the firm's survival rate: while the synergy channel suggests a higher likelihood of survival due to improved startup growth prospects, the anti-competition mechanism predicts a lower survival rate. To the extent that CVC investments in early stage deals increases the likelihood of startup failure, the evidence would support anti-competition effects rather than synergy.

5.4 Exit by CVC Market Dominance

The influence CVC can exert on a startup also varies depending on the its power as an investor. While a CVC new to an industry might be more inclined to learn and experiment, whereas an established CVC with market dominance is more likely to have anti-competitive incentives and greater bargaining power over startups. Therefore, this section investigates the heterogeneous treatment effects of CVC investment across CVCs with high and low market dominance.

I estimate the 2SLS regression by interacting the CVC investments with indicators of the CVC market dominance indicators for a particular industry. Specifically, I estimate the following regression:

$$\begin{aligned}(1^{st}\text{ Stage})\ & \mathbb{1}(CVC\text{-}startup)_{ijst} \times \mathbb{1}(Dominance)^k_{jt} \\ &= \sum_k IV_{ijst} \times \mathbb{1}(Dominance)^k_{jt} + \mathbb{1}(Dominance)^k_{jt} + \beta_0' X_{it} + \alpha_{st} + u_{ijst}\end{aligned} \tag{13}$$

$$\begin{aligned}(2^{nd}\text{ Stage})\ & Y_{ijst} \\ &= \sum_k \gamma^k \left[\mathbb{1}(\widehat{CVC\text{-}startup})_{ijt} \times \mathbb{1}(Dominance)^k_{jt}\right] + \beta_1' X_{it} + \gamma_{st} + \epsilon_{ijst}\end{aligned} \tag{14}$$

where k indexes high and low market dominance respectively. Market dominance is measured by the total number of deals CVC j invested within the focal industry over the past five years. The High Market Dominance dummy variable is defined to be one if the CVC's invested deals are among the top 10% of the all CVC investors and the variable Low Market Dominance is defined conversely. This specification effectively captures the heterogeneous effects of CVC investing power on the startup exits.

Table VIII presents the estimation results. Column (1) shows the effects of CVC investment on the likelihood of an IPO exit. Both coefficients of $\mathbb{1}(CVC\text{-}startup)\times$ $\mathbb{1}(High\,Dominance)$ and $\mathbb{1}(CVC\text{-}startup)\times$ $\mathbb{1}(Low\,Dominance)$ are significantly positive, although the magnitude of $\mathbb{1}(CVC\text{-}startup)\times$ $\mathbb{1}(High\,Dominance)$ is smaller than its counterpart. An F-test confirms the difference in the magnitude is significant at 1% level. Column (2) and (3) indicate that higher CVC market dominance also significantly attenuates the positive effects of CVC investment, as evidenced by a decreasing exit failure rate (statistically insignifican) and an increasing rate of acquisition exits (significant at 5% level). Overall, the results in this section suggest that the positive effects of CVC investment diminish with increased CVC market dominance, consistent with the anti-competition effects.

6 Effects of CVC Investments on Startup Innovation

A key mechanism of creative destruction is the development of disruptive technologies by startups that challenge incumbents' market power. Thus, it is essential to examine whether corporate venture capital (CVC) investments influence the innovation of startups, particularly in areas related to the incumbents' dominant markets.

The effects of CVC investments on startup innovations depend on the type of innovation relative to the CVC parent. On the one hand, disruptive innovations closely related to the CVC parent's product market may pose a threat, incentivizing the parent to redirect the startup's R&D efforts reduce the startup's production of such patents. On the other hand, startups may develop innovations that complement CVC parent's *existing* products and technologies. In addition, the startups may also innovate in *new* product markets where the CVC parent is not currently active, allowing the CVC parent to benefit from knowledge spillovers and better prepare for potential future expansion into those markets. Therefore, the CVC investment may encourage the startup to produce more innovations of such kind.

To assess the extent to which a startup's innovation is disruptive to the CVC's existing product market, I employs the RETech measure developed by Bowen III et al. (2022).

This measure utilizes textual analysis to quantify the degree to which patents pertains to rapidly evolving area of technologies that substitute for existing ones. In their research, high RETech innovations are shown to substitute existing technologies, whereas low RETech innovations tend to complement them.

To establish the relationship between startup patents and the CVC parent's existing product market, I use the patent class-NAICS crosswalks provided by Goldschlag et al. (2016). The authors employ an "Algorithmic Links with Probabilities" (ALP) method, which uses textual analysis of patent abstracts and industry classification keywords to generate probabilistic concordances between patent classes and industries. For each CVC-year, I identify the set of 3-digit NAICS codes representing the CVC parent segments up to the focal year and match them to the corresponding 4-digit Cooperative Patent Classification (CPC) patent classes.

For each startup-CVC pair, I categorize the startup's patents into four distinct groups along two dimensions. First, I classify patents based on whether they are related to the CVC parent's product market ("CVC-related/unrelated"), determined by whether their patent classes are associated with at least one of the CVC parent's industry segments. Second, I classify patents as either disruptive or complementary based on their RETech score. I define a patent as disruptive if its RETech score is above 90^{th} percencile across all patents. This approach yields four CVC-specific patent groups: "*CVC-related disruptive*", "*CVC-related complementary*", "*CVC-unrelated disruptive*", and "*CVC-unrelated complementary*". For each startup-CVC-year, I count the number of newly filed patents within these four categories over the subsequent five years. I estimate how these patent counts are affected by CVC investments at various investment stages using a similar specification as Section 5.3.

Table IX presents the 2SLS estimation results for the effects of CVC investments on the patent counts across four patent categories. Interestingly, the findings varies not only by investment stages, but also varies by the type of innovation. Column (1) indicates that receiving early-stage CVC investment significantly reduces the startup's production of disruptive innovations in CVC-related patent classes. However, no significant reduction is observed in other patent categories. The results indicates that incumbents may be using these investments to redirect the startup's R&D focus away from disruptive technologies in their core markets. The timing in the reduction in disruptive innovations aligns with the reduction in the IPO exit likelihood found in earlier sections, curbing disruptive innovations may be one channel through which CVC investments hinder early-stage startups from establishing themselves as independent players in future product markets.

In contrast, column (3) and (4) show a significant increase in both disruptive and complementary patenting in CVC-unrelated fields following late-stage CVC investments. This reflects the CVC parent's incentive in fostering innovation outside its core market, facilitating knowledge spillovers, and enabling diversification into new markets. Combined with the earlier results that evidence that late-stage CVC investments boost IPO likelihood and reduce failure rates, it suggests that such investments provide startups with the resources and strategic guidance needed to expand their technological frontiers without posing a direct threat to the CVC parent's existing market position.

Column (2) shows that there is also a slight increase in the complementary patenting in CVC-related fields when startup receives late-stage CVC investments, though this effect is only marginally significant at the 10% level. This marginal increase in complementary innovation within CVC-related fields at the late investment stage further supports the idea that CVC investments can facilitate complementary innovations that enhance the parent's existing technologies. Such innovations may help the CVC parent strengthen and extend its market position without the risk posed by disruptive technologies. Robustness checks using Inverse Hyperbolic Transformed dependent variables provided in Appendix Table B.8 show similar results.

Overall, these results support the view that CVC investments play a dual role: curbing potentially threatening disruptive innovations in core markets while fostering innovation in unrelated or complementary areas.

7 Robustness Tests

This section provides robustness checks to the main results presented above. First, to alleviate the concern that the endogenous share component with CVC-startup matching drives the power of the instrument, I apply the "recentering treatment" method proposed by Borusyak and Hull (2023). This technique corrects biases arising from different observations receiving systematically different treatments because of their individual nonrandom "exposure" to the exogenous shock. The main concept is to calculate an "expected" instrument based on permuted shocks and original exposure, and then generate the "recentered" instrument by subtracting the realized instrument from the expected one. To conduct this analysis, for each CVC-startup-year obesrvation, I calculate the expected treatment as the average of the products between the focal ex ante probability and every realized cash flow shocks from the sample. The recentered IV is then calculated by subtracting the realized instrument from the expected treatment calculated from the previous step. Table B.6 shows the results estimated using the recentered IV and the results are robust to this alternative definition of IV.

Second, to further restrict the variations of endogenous share component from driving the power of the instrument, I conduct a battery of robustness tests with subsamples of startups with high ex ante predicted probabilities only. If the results are primarily driven by variations in endogenous ex ante predicted probabilities, we would not expect the instrument to yield significant results within these subsamples, where the predicted probabilities are tightely restricted and the majority of the variation arises from the shock component. Specifically, for each CVC-startup, I rank the startups by the startup's highest ex ante predicted probability across the years, and re-estimate the IV regressions within subsamples of startups that are within top 40%, 30%, 20%, and 10% percentiles, repectively. Table B.6 presents the results estimated within these high ex ante predicted probability subsamples, and the results are robust to this alternative definition of IV.

Third, the main analysis restricts the sample to startups with at least ten years of observation before exit to reduce truncation bias, effectively limiting the sample to observations up to 2012. This 10-year cutoff is based on the average duration from the first funding deal to exit, with a median of 8 years and a mean of 8.6 years. However, a potential concern is that this cutoff omits recent observations where CVC activities are more prevalent. To provide robustness with a more recent sample, I conduct the analysis using an 5-year duration cutoff. Tables B.7 demonstrate that the estimation results remain consistent with this alternative cutoff.

Finally, the innovation tests use patent counts as the dependent variable, but concerns about the skewness of the count data may arise. To address this potential skewness, I perform the regression estimation using the inverse hyperbolic sine (IHS) transformed patent count as the dependent variable. Table B.8 demonstrates that the results are robust to this alternative specification.

8 Conclusion

Corporate Venture Capitals (CVCs) are in-house venture capital funds fully-sponsored by corporations to make minority equity investments in startups. CVCs serve two roles – on one hand, as financial investors, they seek financial returns like other VCs; on the other hand, as an investment arm of a corporation, they serve the strategic objectives of the parent corporation. These objectives may include knowledge transfer or creating synergies, but it could also include mitigating competition from startups.

CVCs have gained prevalence in venture capital, with CVC-backed deals representing 20% of all transactions in 2021 and 70% of Fortune 100 companies having CVC units. Unlike majority acquisitions, CVCs allow firms to gain strategic benefits through small minority stakes, offering access to startups' strategies and technologies without full ownership. This makes them a cost-effective option, but has also led to regulatory scrutiny, particularly around antitrust concerns like the DOJ's enforcement of the "no interlocking directorates" rule, though CVCs still influence startups through other means.

This paper analyzes 1,941 CVC funds and 62,065 startups that received financing between 1982 and 2023. To address selection bias, where CVC-backed startups may differ from others, an instrumental variables (IV) approach is employed. The study leverages the fact that CVCs invest from their parent company's balance sheet, making funding contingent on the parent's cash flow. Segment-level cash flow shocks of the CVC parent, unrelated to the startup's industry, are used as exogenous variation in CVC funding, and these shocks are applied to startups based on their prior exposure to CVC funding shocks.

Using the IV approach, this paper studies the effects of Corporate Venture Capital on startup exit outcomes and innovation. It highlights how CVC can affect startup success by reducing failure rate and boosting the likelihood of IPO. The paper finds that the positive effect of CVC is not confined to just providing additional funding that fills in some funding gap of traditional VCs – although the funding source helps firms that struggle between failure and survival more – the CVC effects also exist because CVCs provide unique supports and resources that traditional VC cannot substitute. The more striking result from the paper comes from the fact that it identifies two scenarios where the CVC anti-competition effects dominate– specifically when CVC has a greater control over the startups. First, when CVC invests in early-stage (pre-A Series) startups, the positive effects are reversed and startups experience both a lower likelihood of IPO and higher chance of failure. Second, the positive effects of CVC investment diminish if the CVC has greater dominance in investing in the startup industry.

The paper also explores a key channel through which anti-competition effects of CVC manifest – by influencing startup innovation. It shows that early-stage startups produce fewer disruptive innovations after CVC investments, but only in areas tied to the CVC's product market. In contrast, late-stage CVC investments boost complementary patents in CVC-related fields and overall patent output in non-CVC fields. This suggests that CVCs both suppress disruptive innovations that could threaten the parent firm's core business and encourage innovations in complementary or unrelated areas.

Overall, the paper provides a nuanced view of CVC investments – CVC investments overall play a positive role in startup success, but its capability to induce conflicts of interest in diverting entry increases with its excessive control of the startup. Entrepreneurs and policy makers ought to understand these nuances when thinking about the implications of CVC investments.

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Figure I. Startup Exit Outcomes by Year of First Funding The table reports the exit outcomes of startups with first funding deal between 1982 and 2012. This figure shows the fractions of startups that have an IPO exit, acquisition exit, failed exit, or remain private as of the of the current sample. We observe exits through 2022, so the sample is ended to allow at least 10 years to observe the exits.

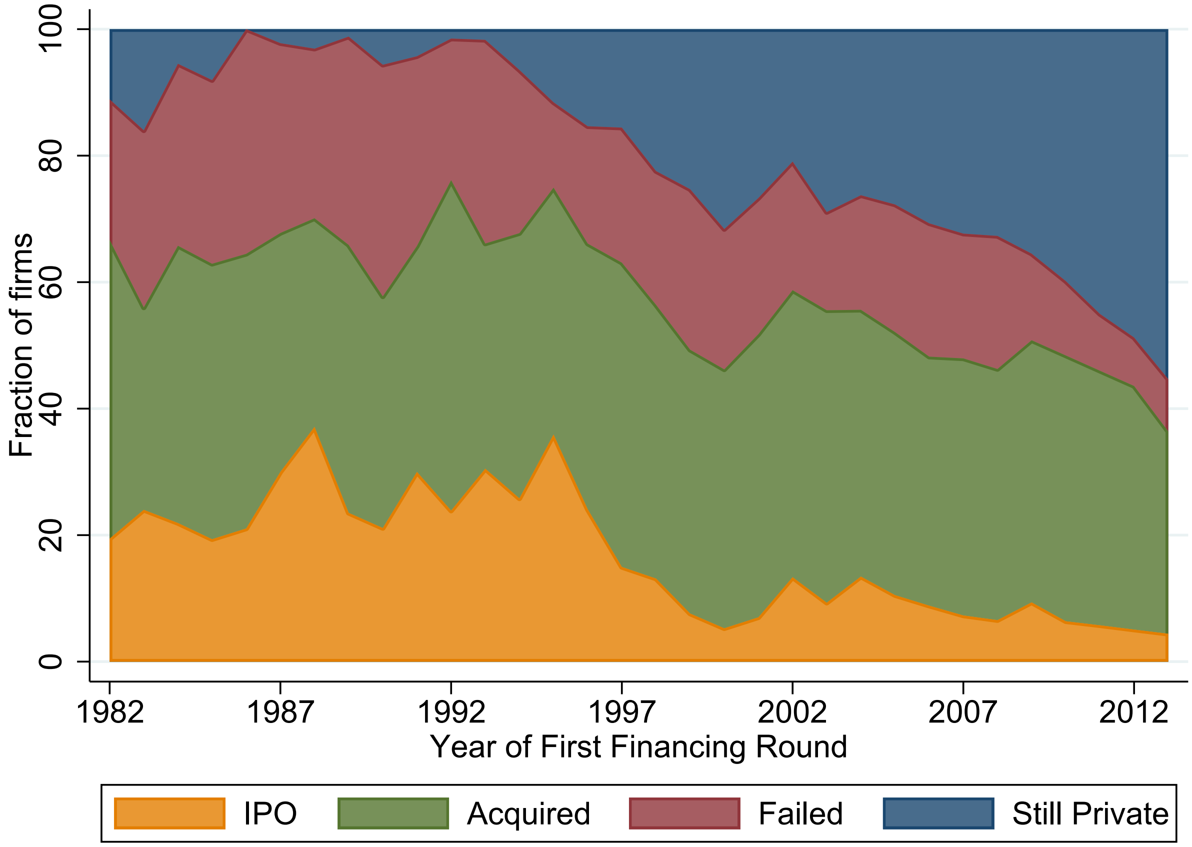

Figure II. Startup Annual Deal Volumes. The figure shows the startup equity financing volume, for deals with or without at least one CVC investors, respectivley. The value is the inflation-adjusted deal size in 2000 USD.

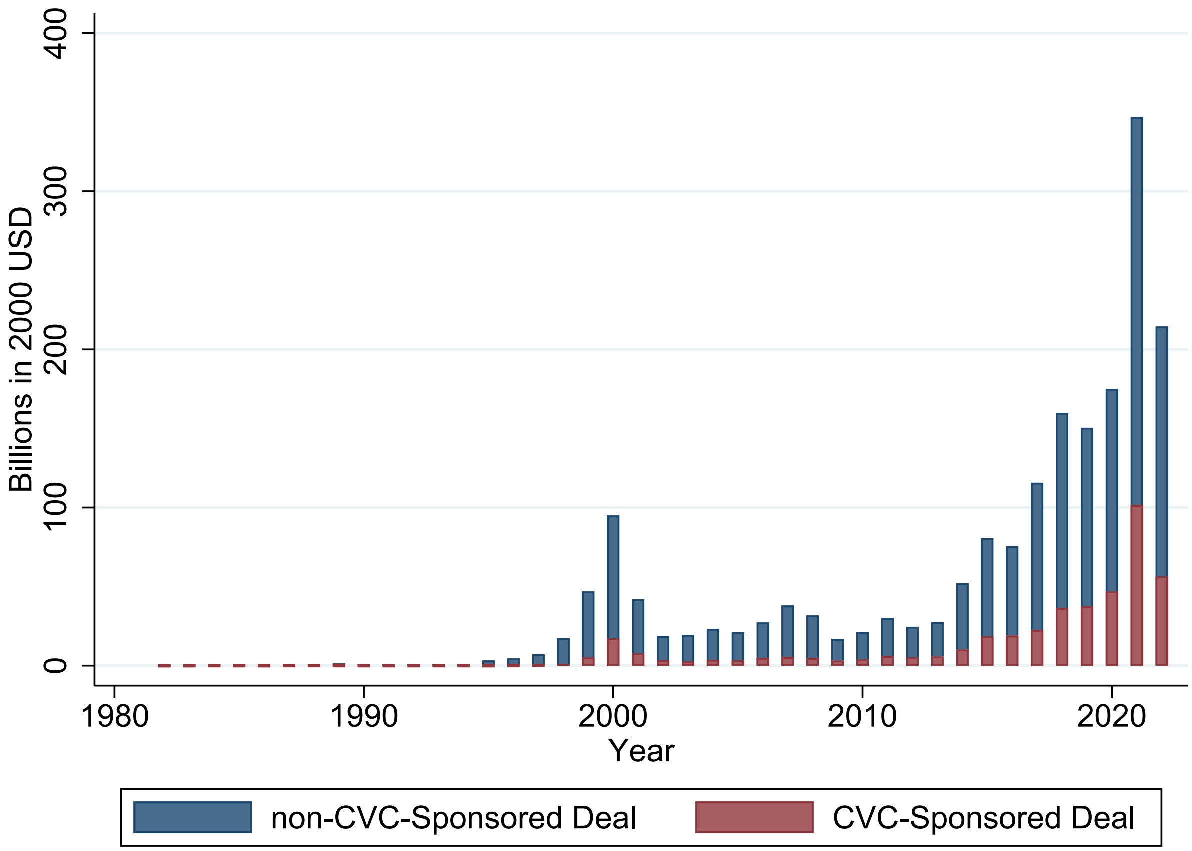

Table I. Startup Exit Outcomes

The table shows the distribution of startup exit outcomes in the sample. Panel A shows the exit outcomes at the startup-level, using the sample of the universe of startups. Panel B shows the startup exit outcomes by last funding rounds. Panel C shows the acquirer type of acquisition exits at the startup-CVC level, where the sample is constructed as follows. For each CVC-subindustry in which the CVC investments are made, I obtain the dates of its initial and final startup equity financing deals, thereby generate a panel of CVC-subindustry-year spanning all the years between the first and last deal date. Next, I include all the startups from the subindustry that are active in the focal year. The summary statistics are drown from unique CVC-startup pairs from the panel. Note that the sample include CVC and the universe of startups satisfying above criteria, including those that are not actually invested by CVC.

Panel A: Startup-level

	Frequency	%
IPO	1756	10.09
Acq	7135	40.99
Failed	3252	18.68
Active	5264	30.24

Panel B: Startup Exit Outcomes (by last funding round)

	IPO (%)	Acq (%)	Failed (%)	Active (%)
Angel	5.43	26.24	15.38	52.94
Pre-Seed	0.00	50.00	0.00	50.00
Seed	3.03	37.88	23.11	35.98
Series A	4.93	40.83	24.47	29.77
Series B	6.51	43.49	19.67	30.33
Series C	9.83	44.71	18.97	26.49
Series D	13.68	43.13	17.50	25.68
Series E	15.88	42.34	15.88	25.91
Series F	21.88	33.52	10.51	34.09
Series G+	31.64	24.36	11.64	32.36

Panel C: Acquirer Type by CVC-startup pair level

Acquirer Type	All startups	CVC-invested startups
CVC parent	0.12%	3.03%
CVC parent competitor (SIC 4 digit)	7.05%*	11.41%*
CVC parent competitor (SIC 3 digit)	14.01%*	18.9%*
CVC parent competitor (SIC 2 digit)	18.07%*	25.65%*

*Only within sample of which acquirers have matched SIC codes from Compustat.

Table II. CVC Investment Distributions

The table shows the summary statistics of the startup equity financing deals invested by CVC, broken down by funding round. Panel A shows the frequency of CVC-invested deals by funding round and its percentage from the total number of CVC invested deals. Panel B shows the distribution of CVC- and non-CVC-invested deals as a percentage of the total number of deals for each funding round.

Panel A: CVC-Invested Deals Funding Round Distribution

Funding Rounds	Frequency	Percent
Angel	14	0.05%
Pre-Seed	54	0.21%
Seed	261	1.01%
Seed VC	4121	15.98%
Series A	7217	27.99%
Series B	6001	23.27%
Series C	3488	13.53%
Series D	1707	6.62%
Series E	733	2.84%
Series F	242	0.94%
Series G	86	0.33%
Series H	38	0.15%
Series I	11	0.04%
Series J	7	0.03%
Series K	3	0.01%
Unclassified	1805	7%

Panel B: Distribution of CVC-Invested Deals vs. Non-CVC-Invested Deals

Funding Rounds	CVC Invested?	
	Yes	No
Angel	0.20%	99.80%
Pre-Seed	5.70%	94.30%
Seed	1.60%	98.40%
Seed VC	14.26%	85.74%
Series A	15.47%	84.53%
Series B	21.35%	78.65%
Series C	23.89%	76.11%
Series D	24.95%	75.05%
Series E	24.74%	75.26%
Series F	22.32%	77.68%
Series G	19.37%	80.63%
Series H	21.84%	78.16%
Series I	15.49%	84.51%
Series J	18.92%	81.08%
Series K	18.75%	81.25%
Unclassified	14.54%	85.46%

Table III. CVC Investment Styles

The table shows the regression results related to CVC investment styles. Panel A shows the CVC's likelihood of being a sole investor of a deal. The sample includes all deal-investor pair information for all startup equity financing deals in the sample. The dependent variable, D(Sole Investor), is a dummy variable that takes the value of one if the focal investor is the only investor of the deal, and zero otherwise. The independent variable, CVC, takes the value of one of the focal investor is a CVC investor, and zero otherwise. Follow-up Deal is a dummy variable is a dummy variable that takes the value of one if the focal investor is not the first deal of an investment stage, judging from the deal date. An investment stage is defined using the Simplified Round variable from CB Insights that classifies the startup equity financing deals into "Angel", "Pre-Seed", "Seed", "Seed VC", "Series A", "Series B", "Series C", "Series D", "Series E+", "Venture Capital" (unclassified). Panel B shows the regression results of CVC investor identity on deal valuation. Valuation is a variable that indicates the deal implied post-money valuation, inflation-adjusted to million USD in 2000 year term. The independent variables CVC and Sole Investors are defined similarly to Panel A. Both regressions also include Round fixed effects and robust standard errors are reported in the parenthesis.

Panel A: Probability of Being a Sole Investor

	D(Sole Investor)	
	(1)	(2)
CVC	0.00636***	-0.00773***
	(0.00171)	(0.00187)
CVC * Follow-up Deal		0.0782***
		(0.00455)
Follow-up Deal		0.0166***
		(0.00131)
Constant	0.0970***	0.0942***
	(0.000453)	(0.000488)
Obs	443,762	443,251
Adjusted-R^2	0.038	0.038
Round Fixed Effects	Yes	Yes
Econ. Mag. [CVC]	0.0628	
Econ. Mag. [CVC * Follow-up Deal]		0.773

Panel B: Deal Valuation

	Valuation (1)	Valuation (2)
CVC * Sole Investor [A]	142.6**	37.60*
	(63.41)	(22.01)
CVC [B]	-64.16***	0.00142
	(14.36)	(2.144)
Sole Investor [C]	-44.78***	-25.28***
	(14.48)	(7.043)
Constant	257.5***	261.2***
	(3.710)	(0.491)
Obs	193,806	182,735
Adjusted-R^2	0.082	0.988
Round Fixed Effects	Yes	
Firm-Round Fixed Effects		Yes
Econ. Mag.[A+B+C]	0.134	0.0491

Table IV. IV First Stage

The table shows the first stage of the 2SLS regression used to analyze startup exit outcomes. The dependent variable is the endogenous variable, 1(CVC-startup), which is a dummy variable equal to one if the focal CVC invests in the focal startup in the current year t. The main independent variable of interest is IV, which is the instrumental variable defined in Section 4.1. The regression include a set of time-varying control variables, including startup age, as well as controls from year t-2, including patent stock, patent citations and growth rates, funding size over the past 1, 2, and 3 years, and the number of peer startups within the focal industry. The standard errors are double clustered at the startup industry level and the CVC-industry-year level. The t-statistics are reported in the parenthesis.

	1(CVC-startup) (1)
IV	0.073***
	(5.41)
Firm Age	-0.00035***
	(-3.18)
Num. Peers within Industry	0.0000019
	(0.37)
Patent Stock [$\leq$ t-1]	-0.000022
	(-0.78)
Past 3 year Patent Stock Growth Rate	0.00038
	(0.72)
past 3 year Patent Citation Grwoth Rate	0.00043
	(0.56)
Past 1-Year Total Funding Raised	0.000015
	(1.64)
Past 3-Year Total Funding Raised	-0.0000060
	(-0.70)
Past 2-Year Total Funding Raised	0.000015
	(1.15)
Constant	0.0072***
	(7.98)
Obs	140,813
Ajusted-R^2	0.03
Y mean	0.0068
Kleibergen-Paap F-stat	29.3
Controls	Yes
Ind-Year FE	Yes

Table V. Baseline Regression: CVC Investments on Exit Outcomes

The table reports the regression results of the effects of CVC investment on various exit outcomes. The sample includes CVC-startup-year observations for each CVC-subindustry-year between its first and last investments in the subindustry and the startups from the subindustry that are active in the focal year. The dependent variable is a dummy variable that takes the value of one if the exit has an exit by IPO (Panel A), Failed (Panel B), Acquisition (Panel C) and Acquisition by CVC parent (Panel D). The independent variable, 1(CVC-startup), is the endogenous variable that takes the value of one if the CVC invests in the startup in the current year. The IV, is the instrumental variable defined in Section 4.1. For each table, Column (1) presents the OLS regression results where the dependent variable is directly regressed on the endogenous variable 1(CVC-startup). Column (2) and (3) presents the Two-stage Least Square (2SLS) IV regression results, where in Column (2) the endogenous variable 1(CVC-startup) is regressed on the IV, and in Column (3), the exit outcome dependent variable is regressed on the instrumented endogenous variable 1(CVC-startup). In Column (4), the dependent variable is regressed directly on the IV. All regressions also include Startup Industry-Year fixed effects. All regressions also include a set of time-varying control variables, including startup age, as well as controls from year t-2, including patent stock, patent citations and growth rates, funding size over the past 1, 2, and 3 years, and the number of peer startups within the focal industry. The standard errors are double clustered at the startup industry level and the CVC-industry-year level. The t-statistics are reported in the parenthesis.

Panel A: IPO

	IPO			
	OLS	IV First Stage	IV Second Stage	IV Reduced Form
	(1)	(2)	(3)	(4)
1(CVC-startup)	0.10***		2.87***	
	(4.63)		(4.11)	
IV		0.073***		0.21***
		(5.41)		(4.61)
Obs	140,813	140,813	140,813	140,813
Ajusted-R^2	0.13	0.03		0.13
Y mean	0.14	0.0068	0.14	0.14
First Stage F-stat		29.3		
Controls	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes

Panel B: Failed

	Failed			
	OLS	IV First Stage	IV Second Stage	IV Reduced Form
	(1)	(2)	(3)	(4)
1(CVC-startup)	-0.073***		-1.73**	
	(-4.05)		(-2.48)	
IV		0.073***		-0.13***
		(5.41)		(-2.61)
Obs	140,813	140,813	140,813	140,813
Ajusted-R^2	0.11	0.03		0.11
Y mean	0.26	0.0068	0.26	0.26
First Stage F-stat		29.3		
Controls	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes

Panel C: Acquisition

	Acquisition			
	OLS	IV First Stage	IV Second Stage	IV Reduced Form
	(1)	(2)	(3)	(4)
1(CVC-startup)	-0.028		-1.14*	
	(-1.17)		(-1.77)	
IV		0.073***		-0.083*
		(5.41)		(-1.78)
Obs	140,813	140,813	140,813	140,813
Ajusted-R^2	0.16	0.03		0.16
Y mean	0.60	0.0068	0.60	0.60
First Stage F-stat		29.3		
Controls	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes

Panel D: Acquisition (CVC Parent)

	Acq (CVC Parent)			
	OLS	IV First Stage	IV Second Stage	IV Reduced Form
	(1)	(2)	(3)	(4)
1(CVC-startup)	0.022***		0.44**	
	(4.20)		(2.26)	
IV		0.073***		0.032***
		(5.41)		(2.69)
Obs	140,813	140,813	140,813	140,813
Ajusted-R^2	0.01	0.03		0.01
Y mean	0.0015	0.0068	0.0015	0.0015
First Stage F-stat		29.3		
Controls	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes

Table VI. Exit Outcomes with Additional Funding Size Control

The table reports the second stage of the 2SLS regression results of the effects of CVC investment on various exit outcomes with the same specification to Table V and additional control variable startup total funding size of concurrent year. The exit outcome dependent variable is regressed on the instrumented endogenous variable 1(CVC-startup). All regressions also include Startup Industry-Year fixed effects. All regressions also include a set of time-varying control variables, including startup age, as well as controls from year t-2, including patent stock, patent citations and growth rates, funding size over the past 1, 2, and 3 years, the number of peer startups within the focal industry and specific to this table, startup total funding size of concurrent year. The standard errors are double clustered at the startup industry level and the CVC-industry-year level. The t-statistics are reported in the parenthesis.

	Failed	IPO	Acq	Acq (CVC Parent)
	(1)	(2)	(3)	(4)
1(CVC-startup)	-0.34	0.99***	-0.65*	0.11
	(-1.09)	(2.77)	(-1.97)	(1.58)
Obs	45,092	45,092	45,092	45,092
Y mean	0.26	0.14	0.60	0.0015
First Stage F-stat	23.5	23.5	23.5	23.5
Controls	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes

Table VII. Startup Exit by Investment Rounds

The table reports the estimation results of a Two-stage Least Square regression of the effects of CVC investment on startup exit outcomes, separately for various investment stages. Panel A reports the first stage regression results. The interacted variable $1(CVC - startup) \times 1(Stage^k)$ is regressed on a set of interactions between instrument IV and the set of $1(Stage^k)$ dummies where $1(Stage^k)$ is defined as Pre-A Rounds, A-C Rounds, and Post-C Rounds, respectively. Panel B reports the estimation results of the second stages. The dependent variable is a dummy variable that takes the value of one if the exit has an exit by Failed (Panel A), IPO (Panel B), Acquisition (Panel C) and Acquisition by CVC parent (Panel D). In the second stage, the dependent variable is regressed on the set of instrumented interaction terms $1(CVC - startup) \times 1(Stage^k)$. All regressions also include a set of time-varying control variables, including startup age, as well as controls from year t-2, including patent stock, patent citations and growth rates, funding size over the past 1, 2, and 3 years, and the number of peer startups within the focal industry. The standard errors are double clustered at the startup industry level and the CVC-industry-year level. The t-statistics are reported in the parenthesis.

Panel A: IV First Stage

	1(CVC-startup) × ...		
	(Pre-A Rounds) (1)	(A-C Rounds) (2)	(Post-C Rounds) (3)
IV × (Pre-A Rounds)	0.058*	-0.0026	-0.0041
	(1.79)	(-0.22)	(-1.50)
IV × (A-C Rounds)	0.00039	0.070***	-0.0032
	(0.25)	(4.00)	(-1.12)
IV × (Post-C Rounds)	0.00070	0.012**	0.092***
	(0.74)	(2.31)	(3.26)
Obs	140,813	140,813	140,813
control	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes

Panel B: IV Second Stage

	Failed	IPO	Acq	Acq (CVC Parent)
	(1)	(2)	(3)	(4)
1(CVC-startup) × (Pre-A Rounds)	10.8***	-10.9***	0.10	0.41**
	(2.99)	(-3.58)	(0.04)	(2.02)
1(CVC-startup) × (A-C Rounds)	2.03	-1.51	-0.53	0.35***
	(1.00)	(-1.19)	(-0.32)	(3.03)
1(CVC-startup) × (Post-C Rounds)	-1.22	11.5***	-10.3***	0.19**
	(-0.68)	(5.04)	(-5.25)	(2.22)
Obs	140,813	140,813	140,813	140,813
Y mean	0.26	0.14	0.60	0.0015
First Stage F-stat	14.4	14.4	14.4	14.4
Controls	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes

Table VIII. Startup Exits by CVC Market Dominance

The table reports the estimation results of a Two-stage Least Square regression of the effects of CVC investment on startup exit outcomes, separately for various investment stages. Panel A reports the first stage regression results. The interacted variable $1(CVC-startup)\times$ *High Dominance* is regressed on a set of interactions between instrument IV and two dummy variables *High Dominance* and *Low Dominance* respectively. Variable *High Dominance* is defined to be one if the CVC's total number of invested deals are among top 10% of all CVC investors in the focal statrtup industry, and zero otherwise. Variable *Low Dominance* is defined reversely. Panel B reports the estimation results of the second stages. The dependent variable is a dummy variable that takes the value of one if the exit has an exit by IPO, Failed, Acquisition and Acquisition by CVC parent. In the second stage, the dependent variable is regressed on the two instrumented interaction terms $1(CVC-startup)\times$ *High Dominance* and $1(CVC-startup)\times$ *Low Dominance*. All regressions also include a set of time-varying control variables, including startup age, as well as controls from year t-2, including patent stock, patent citations and growth rates, funding size over the past 1, 2, and 3 years, and the number of peer startups within the focal industry. The standard errors are double clustered at the startup industry level and the CVC-industry-year level. The t-statistics are reported in the parenthesis.

Panel A: IV First Stage

	1(CVC-startup) × ...	
	High Dominance (1)	Low Dominance (2)
IV × High Dominance	0.14***	-0.0017
	(4.77)	(-0.21)
IV × Low Dominance	0.00051	0.040***
	(0.30)	(3.44)
Obs	140,813	140,813
Control	Yes	Yes
Ind-Year FE	Yes	Yes

Panel B: IV Second Stage

	IPO	Failed	Acq	Acq (CVC Parent)
	(1)	(2)	(3)	(4)
1(CVC-startup) × High Dominance [A]	2.30***	-1.51**	-0.79	0.31**
	(3.88)	(-2.59)	(-1.43)	(2.27)
1(CVC-startup) × Low Dominance [B]	4.41***	-2.56**	-1.84**	0.45
	(3.72)	(-2.12)	(-2.00)	(1.56)
Obs	140,813	140,813	140,813	140,813
Y mean	0.14	0.26	0.60	0.0015
First Stage F-stat	8.76	8.76	8.76	8.76
Coefficients [A]-[B]	-2.10	1.05	1.05	-0.14
Coefficients [A]-[B] p-stat	0.0076	0.14	0.016	0.48
Controls	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes

Table IX. Startup Innovation Disruptiveness by Investment Rounds

The table reports the estimation results of a Two-stage Least Square regression of the effects of CVC investment on startup innovation outcomes, separately for various investment stages. Panel A reports the first stage regression results. The interacted variable $1(CVC-startup)\times 1(Stage^k)$ is regressed on a set of interactions between instrument IV and the set of $1(Stage^k)$ dummies where $1(Stage^k)$ is defined as Pre-A Rounds, A-C Rounds, and Post-C Rounds, respectively. Panel B reports the estimation results of the second stages. The dependent variable is patent count variables that reflects the focal startup's filed patents in the subsequent five years, falling into four categories: *CVC-Related Disruptive* (Column (1)), *CVC-Related Complementary* (Column (2)), *CVC-Unrelated Disruptive* (Column (3)), and *CVC-Unrelated Complementary* (Column (4)). In the second stage, the dependent variable is regressed on the set of instrumented interaction terms $1(CVC - startup) \times 1(Stage^k)$. All regressions also include a set of time-varying control variables, including startup age, as well as controls from year t-2, including patent stock, patent citations and growth rates, funding size over the past 1, 2, and 3 years, and the number of peer startups within the focal industry. The standard errors are double clustered at the startup industry level and the CVC-industry-year level. The t-statistics are reported in the parenthesis.

Panel A: IV First Stage

	1(CVC-startup) × ...		
	(Pre-A Rounds) (1)	(A-C Rounds) (2)	(Post-C Rounds) (3)
IV × (Pre-A Rounds)	0.061***	-0.047***	-0.0032***
	(8.98)	(-9.37)	(-2.91)
IV × (A-C Rounds)	-0.011***	0.11***	-0.0080***
	(-6.53)	(11.84)	(-5.28)
IV × (Post-C Rounds)	-0.0031**	-0.026***	0.16***
	(-2.49)	(-4.14)	(8.39)
Obs	440,018	440,018	440,018
control	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes

Panel B: IV Second Stage

	CVC-Related		CVC-Unrelated	
	Disruptive	Complementary	Disruptive	Complementary
	(1)	(2)	(3)	(4)
1(CVC-startup) × (Pre-A Rounds)	-5.21**	-43.0	1.85	-10.8
	(-2.16)	(-1.62)	(0.45)	(-0.21)
1(CVC-startup) × (A-C Rounds)	-0.40	-3.76	4.55**	39.4
	(-0.36)	(-0.26)	(2.30)	(1.53)
1(CVC-startup) × (Post-C Rounds)	3.98	43.1*	20.2**	161.2**
	(1.65)	(1.70)	(2.51)	(2.47)
Obs	440,018	440,018	440,018	440,018
Y mean	0.037	0.40	0.025	0.31
First Stage F-stat	24.1	24.1	24.1	24.1
Controls	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes

Appendix A Variable Definition

Variable	Definition
Main Variables	
1(CVC-startup)	Dummy variable equal to one if the focal CVC invests in the focal startup at current year, and zero otherwise.
IV	The product of CVC-industry-year level unrelated cash flow and CVC-startup-year level ex ante predicted probability. See Section 4.1 for a detailed definition.
IPO	Dummy variable equal to one if the startup exit through IPO, and zero otherwise.
Failed	Dummy variable equal to one if the startup goes out of business before any successful exit (IPO or acquisition), and zero otherwise.
Acquisition	Dummy variable equal to one if the startup exit through being acquired, and zero otherwise.
Acquisition (CVC Parent)	Dummy variable equal to one if the startup exit through being acquired by the CVC parent, and zero otherwise.
Deal & Investor Characteristics	
Investment Stage	Defined using the *Simplified Round* variable from CB Insights.
Pre-A Rounds	Dummy variable equal to one if the startup is at Angel, Pre-Seed, Seed, or Seed VC stage.
A-C Rounds	Dummy variable equal to one if the startup is at Series A to C round stage.
Post-C Rounds	Dummy variable equal to one if the startup is after Series C round stage.
Sole Investor	Dummy variable equal to one if the focal investor is the only investor of the deal, and zero otherwise.
Follow-up Deal	Dummy variable equal to one if the focal deal is not the first deal of an investment stage, and zero otherwise.
Valuation	Deal-implied post-money valuation, inflation-adjusted to million USD in 2000 year term.
High Dominance	Dummy variable equal to one if the CVC ranks in top 10% of all CVC investors based on its investment shares in the startup industry over the past 5-year ([t-5,t-1]), and zero otherwise. The investment share is defined as total number of CVC-invested deals over total number of deals in the focal startup industry. Low Dominance is defined conversely.
Industry-Year Deal Flow	Industry-year level total deal flow, inflation-adjusted to million USD in 2000 year term.

Variable	Definition
Startup Characteristics	
Patent Stock [$\leq t$-1]	Total number of granted patents with the issue year on or before year t-1.
Past 3-year Patent Stock Growth Rate	Patent stock growth rate between year t-3 and year t-1. To avoid division by zero, the growth rate is defined as $$\text{Growth Rate} = \frac{X_{t-3} - X_{t-1}}{(X_{t-3} + X_{t-1})/2}$$
Past 3-year Patent Citation Growth Rate	Patent citation growth rate for patents issued before year t-3 and before year t-1. Growth rate formula is defined similarly to patent stock growth rate.
Max/Median Similarity with CVC-invested Startups [$\leq$ t-1]	Maximum/Median similarity with any startups invested by the focal CVC on or before year t-1. Similarity is the TF-IDF textual similarity calculated baesd on startup business description.
Max/Median Similarity with CVC-invested Startups [t-3,t-1]	Max/Median similarity with any startups invested by the focal CVC between year t-3 and t-1. Similarity is the TF-IDF textual similarity calculated baesd on startup business description.
Past 1/2/3-Year Total Funding Raised	Inflation-adjusted total funding raised by the focal startup in the past 1/2/3 year, in million USD.
Num. Peers within Industry	Total number of active startups within the same startup industry.
Firm Age	Number of years since founded year.

Appendix B Additional Figures and Tables

Table B.1. Placebo Test: Unrelated Cash Flow on Industry Deal Flow

This table shows the estimation results of an OLS regression of CVC-industry-year panel. The dependent variable is industry-year level deal flow (inflation adjusted) and the independent variable *Unrelated Cash Flow* is the shock component of the instrument, which is the residuals after purging out industry common shocks. *Unrelated Cash Flow* is rescaled by dividing by 1,000 to facilitate the proper display of coefficients. Column (2) also includes year fixed effects. The standard errors are clustered at the industry-year level. The t-statistics are reported in the parenthesis. The economic magnitude indicates the percentage change in the dependent variable associated with one percent increase in the *Unrelated Cash Flow* from the mean. The dependent variable is a dummy variable that takes the value of one if the exit has an exit by IPO, Failed, Acquisition and Acquisition by CVC parent.

	Industry-Year Deal Flow (inflation-adjusted)	
	(1)	(2)
Unrelated Cash Flow	2.26	-8.17
	(0.36)	(-1.50)
Obs	6,479	6,471
Adjusted R^2	-0.00014	0.23
Y mean	1506.9	1506.9
Econ. Mag.	0.0019	-0.0068
Year Fixed Effects	No	Yes

Table B.2. Unrelated Cash Flow on CVC Parent Future 5-year Fundamentals

This table presents OLS regression results for the CVC-industry-year panel, with each row representing a separate regression. The dependent variables are the CVC parent's future 5-year average fundamentals, including Cash Flow, Payout, ROA, ROE, Sales Growth, Earnings Growth, R&D Growth, Capex Growth, Tobin's Q, and Equity Book-to-Market. The independent variable, *Unrelated Cash Flow*, is the shock component of the instrument, derived as residuals after removing industry common shocks. Each regression includes CVC fixed effects, and standard errors are clustered at the CVC level. The columns report the estimation coefficient, p-value, SE (standard errors), Within R^2 for the independent variable *Unrelated Cash Flow*, and Y Mean for the dependent variable's mean.

Dependent Variable	Coefficient	p Value	SE	Within R^2	Y Mean
Cash Flow	-0.00192	0.293	0.00182	-0.00017	1.024
Payout	-0.00025	0.755	0.00079	-0.00005	0.176
ROA	0.00041	0.162	0.00029	0.0022	0.07
ROE	0.00078	0.425	0.00098	-0.0001	0.225
Sales Growth	-0.00057	0.119	0.00037	0.00004	0.082
Earnings Growth	-0.0328	0.247	0.02822	0.00013	-0.034
R&D Growth	0.00007	0.253	0.00006	0.00134	0.058
Capex Growth	0.00003	0.386	0.00003	0.00016	0.047
Tobin's Q	0.00679	0.111	0.00423	0.00396	2.222
Equity Book-to-marke	-0.00044	0.367	0.00048	0.00025	4.449

Table B.3. Relationship Between the Shock and the Share

The table presents OLS regression results of the unrelated cash flow shock (the shock) on the ex ante predicted probability (the share) with the CVC-startup-year panel. The dependent variables *Unrelated Cash Flow* is the shock part of the instrument. The independent variable, *Ex Ante Predicted Probability*, is the share part of the instrument, in percentage. Each regression also includes startup industry-year fixed effects, and standard errors are doulbe clustered at startup industry level and CVC-industry-year level. The t-statistics are reported in the parenthesis.

	(1)
Ex Ante Predicted Probability (%)	14.2
	(0.74)
Constant	5013.3***
	(39.33)
Obs	241,400
Ajusted-R^2	0.30
Within-R^2	0.00055
Y mean	4985.4
Ind-Year FE	Yes

Table B.4. First Stage by Financial Constraint

The table reports the First Stage Split-sample test by Financial Constraint. For each column, the dependent variable, 1(CVC-startup), is the endogenous variable that takes the value of one if the CVC invests in the startup in the current year. The IV is the instrumental variable defined in Section 4.1. The sample divides observations into high and low financial constraint groups based on CVC-year level Kaplan-Zingales (KZ) index. High KZ Index (Column (1)) includes observations of which the CVC-year is among top quartile while Low KZ Index (Column (2)) includes observations of which the CVC-year is among bottom quartile. All regressions also include Startup Industry-Year fixed effects. All regressions also include a set of time-varying control variables, including startup age, as well as controls from year t-2, including patent stock, patent citations and growth rates, funding size over the past 1, 2, and 3 years, and the number of peer startups within the focal industry. The standard errors are double clustered at the startup industry level and the CVC-industry-year level. The t-statistics are reported in the parenthesis.

	(1) Low KZ Index	(2) High KZ Index
IV	0.039	0.10***
	(1.45)	(2.71)
Obs	22,551	32,027
Ajusted-R^2	0.0088	0.037
Control	Yes	Yes
Ind-Year FE	Yes	Yes

Table B.5. Robustness Test using Recentered IV

The table reports the regression results of the effects of CVC investment on various exit outcomes, using an *Recentered IV* from the "recentering treatment" method proposed by Borusyak and Hull (2023). For each CVC-startup-year obesrvation, the expected treatment is calculated as the average of the products between the focal ex ante probability and every realized cash flow shocks from the sample. The recentered IV is then calculated by subtracting the realized instrument from the expected treatment calculated from the previous step. All regressions also include Startup Industry-Year fixed effects. All regressions also include a set of time-varying control variables, including startup age, as well as controls from year t-2, including patent stock, patent citations and growth rates, funding size over the past 1, 2, and 3 years, and the number of peer startups within the focal industry. The standard errors are double clustered at the startup industry level and the CVC-industry-year level. The t-statistics are reported in the parenthesis.

Panel A: Baseline Regression

	Failed	IPO	Acq	Acq (CVC Parent)
	(1)	(2)	(3)	(4)
1(CVC-startup)	-1.80**	3.37***	-1.56**	0.36***
	(-2.27)	(5.42)	(-2.10)	(2.91)
Obs	140,813	140,813	140,813	140,813
Y mean	0.26	0.13	0.62	0.0024
First Stage F-stat	41.8	41.8	41.8	41.8
Controls	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes
Ind-Founded Year FE	Yes	Yes	Yes	Yes

Panel B: Regression By Investment Stages

	Failed	IPO	Acq	Acq (CVC Parent)
	(1)	(2)	(3)	(4)
1(CVC-startup) × (Pre-A Rounds)	7.97**	-8.06***	0.082	0.41**
	(2.57)	(-3.31)	(0.03)	(2.45)
1(CVC-startup) × (A-C Rounds)	1.17	-0.32	-0.85	0.32***
	(0.64)	(-0.28)	(-0.58)	(3.52)
1(CVC-startup) × (Post-C Rounds)	-1.39	11.4***	-9.98***	0.18**
	(-0.79)	(5.15)	(-5.29)	(2.43)
Obs	140,813	140,813	140,813	140,813
Y mean	0.26	0.13	0.62	0.0024
First Stage F-stat	13.8	13.8	13.8	13.8
Controls	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes
Ind-Founded Year FE	Yes	Yes	Yes	Yes

Panel C: Regression By Investor Market Dominance

	IPO	Failed	Acq	Acq (CVC Parent)
	(1)	(2)	(3)	(4)
1(CVC-startup) × High Dominance [A]	2.85***	-1.65**	-1.21*	0.30***
	(5.71)	(-2.58)	(-1.92)	(2.80)
1(CVC-startup) × Low Dominance [B]	5.18***	-2.69*	-2.49**	0.38**
	(4.35)	(-1.96)	(-2.42)	(2.18)
Obs	140,813	140,813	140,813	140,813
Y mean	0.13	0.26	0.62	0.0024
First Stage F-stat	15.6	15.6	15.6	15.6
Coefficients [A]-[B]	-2.32	1.04	1.28	-0.084
Coefficients [A]-[B] p-stat	0.010	0.20	0.013	0.57
Controls	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes
Ind-Founded Year FE	Yes	Yes	Yes	Yes

Table B.6. High Predicted Probability Startups Subsample Only

The table reports the regression results of the effects of CVC investment on various exit outcomes, with high ex ante predicted probability startups only. Panel A includes startups for each CVC, the highest ex ante predicted probability across years is among top 40%. The sample for Panel B, C and D are defined similarly with cutoff 30%, 20%, and 10%, respectively. All regressions also include Startup Industry-Year fixed effects. All regressions also include a set of time-varying control variables, including startup age, as well as controls from year t-2, including patent stock, patent citations and growth rates, funding size over the past 1, 2, and 3 years, and the number of peer startups within the focal industry. The standard errors are double clustered at the startup industry level and the CVC-industry-year level. The t-statistics are reported in the parenthesis.

Panel A: Top 30% Percent High Ex Ante Predicted Probability

	Failed	IPO	Acq	Acq (CVC Parent)
	(1)	(2)	(3)	(4)
1(CVC-startup)	-1.76**	3.01***	-1.25	0.54*
	(-2.00)	(3.33)	(-1.30)	(1.75)
Obs	48,548	48,548	48,548	48,548
Y mean	0.26	0.15	0.59	0.0018
First Stage F-stat	13.2	13.2	13.2	13.2
Controls	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes

Panel B: Top 40% Percent High Ex Ante Predicted Probability

	Failed	IPO	Acq	Acq (CVC Parent)
	(1)	(2)	(3)	(4)
1(CVC-startup)	-1.02	2.27***	-1.26**	0.46*
	(-1.62)	(3.09)	(-2.08)	(1.81)
Obs	63,636	63,636	63,636	63,636
Y mean	0.25	0.15	0.60	0.0017
First Stage F-stat	16.5	16.5	16.5	16.5
Controls	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes

Panel C: Top 20% Percent High Ex Ante Predicted Probability

	Failed	IPO	Acq	Acq (CVC Parent)
	(1)	(2)	(3)	(4)
1(CVC-startup)	-2.18**	2.74**	-0.56	0.39**
	(-2.31)	(2.18)	(-0.46)	(2.09)
Obs	25,329	25,329	25,329	25,329
Y mean	0.26	0.15	0.59	0.0015
First Stage F-stat	20.1	20.1	20.1	20.1
Controls	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes

Panel D: Top 10% Percent High Ex Ante Predicted Probability

	Failed	IPO	Acq	Acq (CVC Parent)
	(1)	(2)	(3)	(4)
1(CVC-startup)	-2.36**	3.22***	-0.86	0.15
	(-2.01)	(2.67)	(-0.64)	(1.09)
Obs	10,496	10,496	10,496	10,496
Y mean	0.26	0.15	0.59	0.0011
First Stage F-stat	11.9	11.9	11.9	11.9
Controls	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes

Table B.7. Robustness Test: 5-year Post-First Financing Cutoff Baseline Results

The table reports the robustness estimation results of startup exit 2SLS regressions, with an alternative sample screening criteria where startups have at least five years (instead of ten years in the original specification) after first funding deals to observe firm exits. All regressions also include Startup Industry-Year fixed effects. Panel A presents the baseline regression result, Panel B presents the by-stage regression results, while Panel C presents the by-CVC market dominance regression results. All regressions also include a set of time-varying control variables, including startup age, as well as controls from year t-2, including patent stock, patent citations and growth rates, funding size over the past 1, 2, and 3 years, and the number of peer startups within the focal industry. The standard errors are double clustered at the startup industry level and the CVC-industry-year level. The t-statistics are reported in the parenthesis.

Panel A: Baseline Regression

	Failed	IPO	Acq	Acq (CVC Parent)
	(1)	(2)	(3)	(4)
1(CVC-startup)	-3.54***	3.32***	0.22	0.48**
	(-3.44)	(4.58)	(0.29)	(2.41)
Obs	182,953	182,953	182,953	182,953
Y mean	0.25	0.14	0.61	0.0013
First Stage F-stat	34.5	34.5	34.5	34.5
Controls	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes

Panel B: Regression By Investment Stages

	Failed	IPO	Acq	Acq (CVC Parent)
	(1)	(2)	(3)	(4)
1(CVC-startup) × (Pre-A Rounds)	4.34*	-8.50***	4.16	0.71**
	(1.75)	(-3.90)	(1.63)	(2.33)
1(CVC-startup) × (A-C Rounds)	-2.49*	0.55	1.94	0.48***
	(-1.91)	(0.61)	(1.53)	(2.65)
1(CVC-startup) × (Post-C Rounds)	-3.52***	11.7***	-8.16***	0.21*
	(-2.63)	(5.13)	(-4.90)	(1.77)
Obs	182,953	182,953	182,953	182,953
Y mean	0.25	0.14	0.61	0.0013
First Stage F-stat	11.5	11.5	11.5	11.5
Controls	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes

Panel C: Regression By Investor Market Dominance

	IPO	Failed	Acq	Acq (CVC Parent)
	(1)	(2)	(3)	(4)
1(CVC-startup) × High Dominance [A]	3.04***	-3.13***	0.094	0.43**
	(4.18)	(-3.20)	(0.14)	(2.39)
1(CVC-startup) × Low Dominance [B]	4.94***	-4.83***	-0.11	0.35
	(3.84)	(-2.85)	(-0.10)	(1.44)
Obs	182,953	182,953	182,953	182,953
Y mean	0.14	0.25	0.61	0.0013
First Stage F-stat	8.71	8.71	8.71	8.71
Coefficients [A]-[B]	-1.91	1.71	0.20	0.090
Coefficients [A]-[B] p-stat	0.013	0.054	0.62	0.58
Controls	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes

Table B.8. Startup Innovation Disruptiveness (Inverse Hyperbolic Transformed) by Investment Rounds

The table reports the robustness estimation results of Table IX, with inverse hyperbolic transformed patent counts as dependent variables. Panel A reports the first stage regression results. The interacted variable $1(CVC - startup) \times 1(Stage^k)$ is regressed on a set of interactions between instrument IV and the set of $1(Stage^k)$ dummies where $1(Stage^k)$ is defined as Pre-A Rounds, A-C Rounds, and Post-C Rounds, respectively. Panel B reports the estimation results of the second stages. The dependent variable is inverse hyperbolic transformed patent count variables that reflects the focal startup's filed patents in the subsequent five years, falling into four categories: *CVC-Related Disruptive* (Column (1)), *CVC-Related Complementary* (Column (2)), *CVC-Unrelated Disruptive* (Column (3)), and *CVC-Unrelated Complementary* (Column (4)). In the second stage, the dependent variable is regressed on the set of instrumented interaction terms $1(CVC - startup) \times 1(Stage^k)$. All regressions also include a set of time-varying control variables, including startup age, as well as controls from year t-2, including patent stock, patent citations and growth rates, funding size over the past 1, 2, and 3 years, and the number of peer startups within the focal industry. The standard errors are double clustered at the startup industry level and the CVC-industry-year level. The t-statistics are reported in the parenthesis.

Panel A: IV First Stage

	1(CVC-startup) × ...		
	(Pre-A Rounds) (1)	(A-C Rounds) (2)	(Post-C Rounds) (3)
IV × (Pre-A Rounds)	0.061***	-0.047***	-0.0032***
	(8.98)	(-9.37)	(-2.91)
IV × (A-C Rounds)	-0.011***	0.11***	-0.0080***
	(-6.53)	(11.84)	(-5.28)
IV × (Post-C Rounds)	-0.0031**	-0.026***	0.16***
	(-2.49)	(-4.14)	(8.39)
Obs	440,018	440,018	440,018
control	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes

Panel B: IV Second Stage

	CVC-Related		CVC-Unrelated	
	Disruptive	Complementary	Disruptive	Complementary
	(1)	(2)	(3)	(4)
1(CVC-startup) × (Pre-A Rounds)	-1.74*	-6.90	0.92	10.2***
	(-1.96)	(-1.39)	(0.99)	(2.87)
1(CVC-startup) × (A-C Rounds)	-0.049	0.24	2.23***	11.7***
	(-0.11)	(0.09)	(3.29)	(4.73)
1(CVC-startup) × (Post-C Rounds)	1.69*	6.09**	6.47***	21.4***
	(1.93)	(2.18)	(3.17)	(5.44)
Obs	440,018	440,018	440,018	440,018
Y mean	0.016	0.084	0.011	0.069
First Stage F-stat	24.1	24.1	24.1	24.1
Controls	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes