Financing J-Curves in Venture Capital

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ABSTRACT

Startups face a trade-off between short-term profitability and long-term growth. Their cash flows are said to follow a so-called J-curve. The shape of the curve depends on investors' financing capacity: their ability to sustain prolonged periods of negative cash flow. US venture capitalists are often believed to have greater financing capacity. We examine a large Swedish dataset with detailed cash flow information. Swedish startups backed by US venture capitalists experience deeper J-curves, with larger short-term losses and higher long-term sales, relative to those backed by non-US venture capitalists. These results are consistent with US venture capitalists having greater financing capacity: they can provide more funding directly and have better access to later-stage investors.

JEL classification: G24, O16, L26, G32, O31.

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1 Introduction

A large prior literature establishes the importance of venture capital for innovation and economic growth (Da Rin, Hellmann, and Puri 2013; Gompers and Lerner 2001). However, a fundamental challenge for startups seeking to develop new technologies and business models is that doing so requires substantial investments and time. Startups often face a trade-off between short-term profitability and long-term growth. Pursuing rapid expansion typically requires sustained investment and can generate extended periods of negative operating cash flow. As a result, the financial dynamics of high-growth startups are frequently described as following a "J-curve," where early losses precede later growth and successful exits.[1]

Financing such trajectories requires investors with sufficient financing capacity to support companies through these early losses. If investors anticipate that follow-on funding may become unavailable, they may avoid projects that require sustained investment before reaching scale due to financing risk (Nanda and Rhodes-Kropf 2013, 2017). Differences in investors' financing capacity may therefore shape the depth of startup J-curves and the ability of startups to pursue aggressive growth strategies.

Understanding these financing constraints is central to explaining differences in the performance of innovation ecosystems and their ability to generate transformational innovations. A recent influential report by Draghi 2024 argues that Europe's innovation challenge is not the generation of ideas but the ability of companies to scale:

"The problem is not that Europe lacks ideas or ambition (...) But innovation is blocked at the next stage: we are failing to translate innovation into commercialisation, and innovative companies that want to scale up in Europe are hindered at every stage."

This paper provides large-scale empirical evidence on the dynamics of J-curves in VC-backed companies, documents heterogeneity in J-curve depth across investors' geographical origin, and relates this heterogeneity to financing capacity. We focus on a comparison between US and non-US venture capital investors because the US venture capital market is widely viewed as deeper and more mature, with larger funds and broader investor networks, which may allow US investors to provide greater financing

[1] In the context of relationships between limited and general partners, the term J-curve is also used to describe the cash flows of VC funds themselves. In this paper, however, we focus on the relationship between VC funds and the companies they finance. Throughout the paper we therefore apply the term J-curve to the cash flows of the underlying portfolio companies.

capacity. Using detailed administrative data on Swedish startups combined with global venture capital data, we compare companies financed by US and non-US venture capital investors operating in the same entrepreneurial environment.

Using Sweden as a laboratory offers several advantages. Administrative registry data allow us to observe detailed financial information for Swedish VC-backed startups. Unlike in most countries, including the United States, all limited liability private companies in Sweden are required to file annual financial statements with government authorities. This requirement provides comprehensive and reliable company-level data, which are essential for analyzing the cash flow dynamics of VC-backed companies. Sweden also hosts a well-developed venture capital market, providing a diverse setting for studying VC-backed companies. The richness of the data allows us to provide large-scale empirical evidence on the dynamics of J-curves in VC-backed startups and to document heterogeneity in J-curve depth across investors' geographical origin operating in the same entrepreneurial environment.

US VCs do not invest randomly in startups, which raises concerns about selection bias. To address this issue, we follow the established literature on the economic effects of private equity investments and implement a stacked difference-in-differences (DiD) design combined with matching (Agrawal and Tambe 2016; Antoni, Maug, and Obernberger 2019; Baker, Larcker, and Wang 2022; Olsson and Tåg 2017; Roth et al. 2023). Matching uses the rich administrative data to construct comparable cohorts of startups prior to the investment event. The DiD framework differences out unobservable factors that are constant over time, such as persistent differences in startup quality or growth potential. In addition, to assess the plausibility of the identifying assumption, we use the detailed financial data to examine pre-investment trends and verify that treated and control startups exhibit parallel dynamics prior to US VC investment.

Our empirical analysis begins by documenting the prevalence of J-curves in venture capital investing and by examining whether companies backed by US VCs exhibit deeper J-curves. We show that J-curves are a widespread feature of VC-backed companies' financial dynamics. In our sample, 80% of company-year observations exhibit negative operating cash flows. This pattern reflects the fact that venture capital investors specialize in financing startups that incur short-term losses while pursuing large future payoffs. By contrast, most non-VC-funded companies must maintain positive cash flows to remain operational. In this sense, VC-backed startups face a trade-off between riding steeper J-curves that prioritize growth and shallower J-curves that prioritize short-term profitability.

Using the stacked difference-in-differences design described above, we document three main empirical patterns. First, startups backed by US VCs experience larger operating losses after the investment relative to a matched sample of startups funded by non-US VCs. These losses follow a J-curve pattern, increasing during the first several years and recovering thereafter. US VC-backed companies also exhibit deeper J-curves, reflected in larger maximal losses, and wider J-curves, reflected in longer durations of negative cash flows. Second, companies backed by US VCs exhibit larger sales in the long run, but not the short run. Differences become statistically significant approximately three years after the investment. Third, startups funded by US VCs raise substantially more external financing, both at the time of the initial investment and in subsequent funding rounds. Taken together, these patterns indicate that US VC-backed startups sustain deeper J-curves while raising more follow-on capital and achieving stronger long-run growth.

We next examine potential mechanisms that may explain the deeper J-curves observed among US VC-backed companies. Several policy reports discussing the "scale-up gap" in Europe highlight differences in the availability of large venture capital funds between the United States and Europe. For example, research by the European Investment Bank notes that:[2]

The limited availability of large-scale venture capital funds in the European Union makes it harder for EU scaleups to raise capital. Between 2013 and 2023, there were 137 venture capital funds larger than $1 billion in the United States compared with only 11 in the European Union and ten in the United Kingdom. (. . .) EU-based companies struggle to find EU investors with the ability to write big tickets in a large capital funding round.

Motivated by these observations, we examine whether differences in VC fund size are associated with differences in financing capacity and J-curve dynamics. To interpret these patterns, we build on the financing risk framework developed by Nanda and Rhodes-Kropf (2013, 2017). In this framework, investment decisions depend on expectations about the availability of future financing rounds, implying that investors with greater financing capacity may be better positioned to support companies pursuing long and deep J-curves.

[2] See Fratto et al. (2024). For further discussions of the scale-up gap and the role of large funds, see also Hellmann, Frydrych, et al. (2016), Duruflé, Hellmann, and Wilson (2018), Quas et al. (2022) and European Investment Fund (2025).

Consistent with this idea, we find that differences in J-curves between US and non-US investors largely disappear among startups backed by large VC funds. This suggests that once companies are supported by large investors, they can sustain deep J-curves regardless of investor origin. However, differences reappear among startups backed by smaller VC funds, indicating that fund size alone does not fully account for the observed patterns.

The financing risk framework also highlights the importance of access to follow-on investors. Smaller VC funds may face constraints in providing additional capital themselves and therefore rely more heavily on attracting new investors in later financing rounds. Consistent with this mechanism, we find that companies backed by US VCs attract more follow-on investors, particularly among smaller VC funds. These results suggest that US investors may facilitate better access to later-stage financing markets.

Finally, we examine whether exposure to US venture capital practices affects investment dynamics. Specifically, we test whether non-US VCs with prior US co-investments or US limited partners exhibit similar patterns. We find no evidence that prior co-investment with US VCs is associated with deeper J-curves. While non-US VCs with US LPs appear to finance somewhat deeper J-curves, this pattern is largely explained by the fact that US LPs tend to invest in larger VC funds. Taken together, the evidence points to financing capacity arising from both fund size and investor networks as the primary mechanism behind the deeper J-curves associated with US VC-backed companies.

Overall, our analysis contributes to the understanding of J-curves, which have received relatively little attention in the academic literature. We document their prevalence among VC-backed companies and identify important heterogeneity in J-curve dynamics across investors' geographical origin. Our findings suggest that the ability of startups, backed by US VCs, to sustain deeper interim losses is closely related to differences in financing capacity. Two mechanisms appear particularly important. First, US VCs tend to operate larger funds, and larger funds are associated with greater financing capacity. Second, even when US VCs are not large themselves, they have better access to follow-on funding, which is essential for financing long and deep J-curves.

The fact that US VC investors are associated with deeper J-curves provides an additional perspective on why European startup ecosystems continue to lag behind the US in producing large-scale entrepreneurial successes (often referred to as "unicorns"). These types of outcomes typically require substantial financing capacity over extended periods. While no single paper can fully explain differences between US and European venture capital markets, our evidence shows that even within the same entrepreneurial environment, comparable companies backed by US and non-US investors exhibit systematically different cash flow patterns.

This paper contributes to the literature on venture capital and innovation by providing large-scale empirical evidence on J-curves in VC-backed companies. As discussed above, the paper builds on the financing risk framework developed by Nanda and Rhodes-Kropf (2013, 2017). More broadly, our empirical results provide a novel test of the financing risk framework in the context of venture capital investing, linking differences in investors' financing capacity to the ability of startups to sustain prolonged periods of negative cash flow. More specifically, it contributes to this literature in three ways. First, while prior work emphasizes how financing risk affects investment decisions, we examine how investors differ in their ability to manage financing risk. In particular, we distinguish between internal follow-on funding provided by large VC firms and external follow-on funding facilitated through investor networks. Second, whereas Nanda and Rhodes-Kropf (2013) identify financing risk using variation in hot and cold venture capital markets, we use a complementary empirical strategy that exploits heterogeneity across investors and implements a difference-in-differences design. Third, our setting allows us to study these mechanisms in an international context, comparing US and non-US investors operating in the same entrepreneurial environment.

Our analysis also relates to a broader literature documenting the role of venture capital in innovation and company growth. Early work by Kortum and Lerner (2000) and Hellmann and Puri (2000) shows that VC-backed companies are more innovative, while subsequent studies document that VC-backed companies tend to grow faster and exhibit stronger productivity dynamics (Chemmanur, He, et al. 2018; Chemmanur, Krishnan, and Nandy 2011; Croce, Martí, and Murtinu 2013; Puri and Zarutskie 2012).

Another strand of the literature highlights substantial heterogeneity across venture capital investors in their investment practices and outcomes (Bottazzi, Da Rin, and Hellmann 2008, 2016; Gompers, Kovner, et al. 2008; Hochberg, Ljungqvist, and Lu 2007; Sorensen 2007). Our paper contributes to this literature by examining how differences in financing capacity across investors are associated with differences in startup growth dynamics. A central challenge with this is the long-term nature of venture capital investing, where investors accept short-term negative cash flows in the hope of large positive cash flows in the long term. A prior corporate finance literature examines the trade-off between short-vs. long-term cash flows, including the foundational theoretical work by Stein (1989), and key empirical studies by Asker, Farre-Mensa, and Ljungqvist (2015), Ferreira, Manso, and Silva (2014), and Frésard et al. (2025).

Finally, our work relates to the literature on international differences in venture capital markets. The US venture capital market is substantially larger than those in most other countries and has a comparative advantage in scale-up financing (Devigne et al. 2018; Hellmann, Frydrych, et al. 2016). US investors are also associated with stronger exit opportunities, including IPOs and acquisitions (Bertoni and Groh 2014; Conti and Guzman 2023), and may facilitate faster growth through international market access and technology transfer (Akcigit et al. 2024; Carneiro, Moreira, and Sheng 2022; Fernhaber, McDougall-Covin, and Shepherd 2009; Mäkelä and Maula 2005, 2006). Their investor networks can also improve access to capital (Humphery-Jenner and Suchard 2013). Our paper contributes to this literature by showing that, even within a common entrepreneurial environment, companies financed by US and non-US investors exhibit systematically different J-curve dynamics.

The remainder of the paper is organized as follows. Section 2 describes the institutional details and the data. Section 3 outlines the empirical approach. Section 4 presents the main results, while Section 5 investigates the underlying mechanisms. Section 6 provides additional analyses and robustness checks. Section 7 concludes.

2 Institutional details and data

Our empirical analysis draws on administrative data from Sweden. The Swedish institutional environment offers two key advantages for studying post-investment startup dynamics. First, unlike many other countries, including the United States, Sweden mandates that all limited liability companies, regardless of size, submit detailed annual financial statements to government authorities.[3] Second, compliance is strictly enforced: failure to file, or filing incorrect information, can result in liquidation and unlimited personal liability for board members. These incentives generate a comprehensive and reliable accounting database that is accessible for research through the Swedish Companies Registration Office.

This institutional setting allows us to observe financial gains and losses for private companies with

[3] Årsredovisningslag [1995:1554] 8 sec. 3 and Bokföringslag [1999:1078] 6 sec. 2.

a level of precision that is rarely available in other contexts. In particular, it enables a granular analysis of operating losses and recovery dynamics following venture capital investment, which is central to our study of J-curves and financing capacity.

Sweden's venture capital market itself provides a suitable environment for comparative analysis. Sweden ranks among the largest VC markets globally relative to GDP and is a leading country in early-stage financing. The market is mature and diversified, with active participation by domestic and foreign investors, including a substantial presence of US venture capital firms. This coexistence of investor types within a single institutional and regulatory framework allows us to compare investment outcomes across investor origins while holding constant country-level conditions.

More broadly, Sweden's stable macroeconomic environment, transparent legal system, and strong support for innovation make it attractive to international investors (Lerner and Tåg 2013). These features reduce concerns that differences in outcomes reflect institutional frictions rather than investor characteristics. Together, the comprehensive accounting data and the presence of both US and non-US venture capital investors make Sweden a particularly well-suited setting for studying how investor type shapes post-investment startup dynamics.

2.1 Data sources

We use administrative data from the Swedish Companies Registration Office covering the population of limited liability companies between 1998 and 2023.[4] The limited liability company is the dominant organizational form for Swedish startups and is the only form that provides limited liability to all shareholders. The data include complete balance sheets, income statements, and supplementary disclosures.

When both consolidated and unconsolidated accounts are available, we use consolidated statements, as they better capture a company's overall economic activity. We also annualize flow variables to account for differences in fiscal year length. Details on how we construct cash flow statements are provided in

[4]Our analysis is based on company-level financial statement data. A related entrepreneurship literature uses similar data but focuses on other outcomes. Prior work studies how productivity, costs, sales, employment, and payroll evolve under VC ownership (Chemmanur, He, et al. 2018; Chemmanur, Krishnan, and Nandy 2011; Croce, Martí, and Murtinu 2013; Puri and Zarutskie 2012). Other papers examine how investor types affect company performance (Alperovych, Hübner, and Lobet 2015; Colombo and Murtinu 2017), how financing type influences outcomes (Giraudo, Giudici, and Grilli 2019), and how non-executive directors affect company behavior (Montag 2024). Using an accounting approach, Hand (2005) studies the value relevance of financial statements in venture capital. Barrot and Nanda (2020) examine how payment timing affects startup cash flows and employment, while Belenzon, Chatterji, and Daley (2020) analyze growth patterns of European private companies.

Appendix A.

We merge the accounting data with information on venture capital investments and exits from PitchBook, Crunchbase, and VentureXpert. We focus on equity-based VC financing rounds, such as early-stage VC investments and Series A–C rounds. We combine events appearing in multiple databases by keeping mode values of variables (e.g., round amount). We verify that the distribution of days between funding rounds in our "master" VC dataset is similar to the distributions in the individual VC databases.

We match VC events to Swedish startups using company name and city. For companies with a single exact name match in the administrative data, we retain that match. For companies with multiple name matches, we retain the observation with a unique city match. Because our analysis focuses on investor origin, we manually collect the headquarters location of VC firms when this information is missing.

We convert balance sheet, income statement, cash flow statement, and VC investment as well as exit variables to real 2025 Swedish krona (SEK) to account for inflation. Average Euro and US dollar to SEK exchange rates for December 2025 are 10.895 and 9.294, respectively.

3 Empirical strategy and sample construction

3.1 Empirical challenges

A central empirical challenge is that venture capital investors do not select startups randomly. In particular, US venture capital firms may differ from non-US investors in how they screen and select companies, potentially introducing selection bias.

Ex ante, however, there are several reasons to expect that US and non-US VCs investing in Sweden target broadly similar startups. The Swedish entrepreneurial ecosystem is relatively small and transparent, with high-quality startups being visible to both domestic and international investors. Sweden's strong reputation for innovation and its integration into global markets attract substantial foreign investor attention, leading US and non-US VCs to compete for similar investment opportunities. Moreover, Swedish startups seeking VC funding tend to operate in scalable, internationally-oriented sectors that are attractive to investors regardless of origin.

Nevertheless, concerns about differential selection remain. To address them, we follow the established literature on the economic effects of private equity investments and implement a stacked difference-in-differences design combined with matching (Agrawal and Tambe 2016; Antoni, Maug, and Obernberger 2019; Baker, Larcker, and Wang 2022; Olsson and Tåg 2017; Roth et al. 2023). This approach leverages rich administrative data to control for observable differences and absorbs time-invariant unobserved heterogeneity. The key remaining threat to identification comes from time-varying unobservables that differentially affect startups receiving US and non-US VC investment.

3.2 Empirical specification

To do this, we construct event-specific datasets for each year in which US VC investments occur. Each dataset includes startups receiving their first US VC investment in that year and a matched set of companies receiving non-US VC investments in the same year. With US VC investments occurring between 2000 and 2020, we construct 21 event-specific cohorts, which we then stack and align using normalized event time relative to the year of the first US VC investment.

We estimate the following difference-in-differences specification:

$$Y_{s,t,c} = \alpha + \pi \text{Post}_t + \gamma \text{US VC}_{s,c} + \beta \text{Post}_t \times \text{US VC}_{s,c} + \text{C}_c + \varepsilon_{s,t,c}, \tag{1}$$

where $Y_{s,t,c}$ denotes the outcome of startup s in event year t and cohort c. Post_t equals one in the year of investment and all subsequent years, and US $\text{VC}_{s,c}$ equals one for startups receiving their first US VC investment and zero for startups receiving a non-US VC investment in the same year. The interaction term captures differential post-investment dynamics for US VC-backed startups. The coefficient β captures the differential post-investment dynamics associated with US VC investments. To study dynamic patterns, we replace Post_t with event-time indicators ranging from $t-4$ to $t+7$, with $t-1$ as the omitted baseline year. All regressions include cohort fixed effects (C). Standard errors are clustered at the company-by-cohort level to account for repeated appearances of benchmark companies across cohorts.

3.3 Final sample construction

We construct a company–year panel of VC-backed startups, focusing on companies that receive venture capital financing. Our objective is to compare startups receiving their first US VC investment to observationally similar startups receiving non-US VC funding in the same investment year. To do so, we adopt a cohort-based matching approach combined with a stacked difference-in-differences design.[5] Importantly, the matching procedure primarily restricts the control group, preserving the majority of US VC observations while improving comparability.

The sample construction proceeds as follows (see Section B in the Internet Appendix for additional details). First, we restrict the data to startups that have ever received a VC investment. Second, we require startups to have at least one year of pre-investment data, which is the minimum necessary to measure pre-treatment characteristics and implement matching.

Third, for each investment year, we match startups receiving their first US VC investment to startups receiving non-US VC funding in the same year. Matching is performed on four characteristics measured at $t-1$: industry (3 bins), investment stage (3 bins), EBITDA (quartiles), and employment (quartiles). These variables proxy for the key dimensions along which investors may select startups ex ante. Industry and stage capture technology and life-cycle position, while EBITDA and employment capture operating performance and scale. Together, they summarize a startup's position in its development path and its expected demand for external financing, including its capacity to sustain losses while scaling. Matching is implemented on coarsened bins to ensure common support between treated and control companies within each cohort. This design compares startups that are similar along observable dimensions prior to investment and face comparable financing needs at baseline.

Fourth, we exclude startups that have prior US VC exposure but do not receive US VC funding in the focal year. This ensures that the control group consists of startups without US VC involvement at event time zero, yielding a clean comparison between first-time US VC recipients and otherwise similar non-US VC-backed startups.

Finally, we stack the cohort-specific matched samples across investment years and align them in event time. This yields our final estimation sample, which exploits within-cohort variation between US and non-US VC investments among startups that are comparable on pre-treatment observables.

[5] Smith and Todd (2005) show that combining matching with difference-in-differences can substantially reduce selection bias.

3.4 Descriptive statistics

Table 1 presents descriptive statistics comparing startups that receive their first US VC investment to those that receive funding from non-US VCs, measured one year prior to the investment. The table reports means for the full sample (Column 1), US VC-backed startups (Column 2), non-US VC-backed startups (Column 3), the difference in means (Column 4), and the corresponding t-statistics (Column 5). The table is organized into three panels.

Panel A reports the variables used in the matching procedure. These include EBITDA, number of employees, and the VC round number. While matching is implemented on coarsened bins of these variables rather than on exact values, Panel A shows that the resulting samples are well balanced. EBITDA in the full sample is approximately -13 million SEK, with a difference of roughly 1 million SEK between startups that go on to receive US VC funding and those that receive non-US VC funding. This difference is neither economically nor statistically significant. Companies employ, on average, about 16 employees in the year prior to investment; the difference between the two groups is approximately two employees and statistically insignificant. Similarly, startups are at comparable stages in terms of VC round number, with no meaningful differences across groups. Furthermore, a χ^2-test for differences in the distribution of companies receiving initial US VC and non-US VC funding across industries is insignificant with a p-value of 0.69. Overall, Panel A indicates that the matching procedure successfully aligns US and non-US VC-backed startups along key observable pre-investment dimensions.

Panel B reports additional company characteristics that are central to the analysis but are not directly used in the matching procedure. These include operating cash flow, sales, VC funding, and an indicator for having foreign subsidiaries (another indicator of scaling and growth). Despite not being matched on these variables, startups receiving US and non-US VC investments are well balanced. Differences in operating cash flow, sales, and foreign subsidiary presence are small and statistically insignificant. There is a modest difference in prior VC funding levels, which is economically small and not statistically significant. The absence of systematic differences along these dimensions further supports the credibility of the matched control group.

Panel C reports a broader set of observable characteristics, including balance sheet variables and detailed measures of managerial and board experience. These variables are not used for matching but are informative about potential selection on startup quality or team characteristics. On average, companies have total assets of approximately 33 million SEK, an operating return on assets of around −70 percent, and only 14 percent are profitable in the year prior to investment. Roughly 40 percent of startups have previously received VC funding, and 5 percent have received angel funding. Across these dimensions, there are no statistically significant differences between companies receiving US and non-US VC investments. The only variable showing a modest economic difference is operating return on assets, which is slightly lower for startups receiving US VC investments, but this difference is not statistically significant. Panel C also reports detailed measures of managerial and board experience, including prior startup experience, same-industry startup experience, VC experience, and US VC experience for both managers and directors. These variables shed light on whether US VCs systematically select startups based on the background or international exposure of the leadership team. We find no economically or statistically meaningful differences across any of these characteristics. The only minor exception is US VC experience among managers, which is marginally higher for companies receiving non-US VC investments, but the magnitude is economically negligible.

Taken together, Table 1 shows that startups receiving US and non-US VC investments are highly comparable across a wide range of observable characteristics prior to investment. This balance holds not only for variables used in the matching procedure, but also for key outcomes, balance sheet measures, and detailed management and board characteristics. Combined with the absence of differential pre-trends documented in Section 4, these findings support the interpretation that the matched non-US VC group provides a useful counterfactual for assessing the post-investment dynamics of startups receiving US VC funding.

4 J-curves in VC investing

This section presents the baseline results on post-investment dynamics following US and non-US venture capital investments. Figure 1 displays event-time estimates for operating cash flow, sales, and venture capital funding around the first VC investment. Table 2 reports the corresponding regression estimates.

4.1 Operating cash flow

Panel A of Figure 1 plots the evolution of cash from operations, measured in millions of Swedish kronor, relative to the year prior to the first VC investment. The left figure displays raw means, while the right figure displays dynamic event-time estimates. Before investment, startups that later receive US VC funding and those that receive non-US VC funding exhibit parallel trends in operating cash flow, with no statistically or economically meaningful differences between the two groups.

Following investment, however, the dynamics diverge sharply. US VC-backed startups experience a pronounced decline in operating cash flow, reaching a trough approximately five years after the initial investment. At this point, operating cash flow is close to 30 million SEK lower for US VC-backed companies relative to non-US VC-backed companies. This difference is both statistically significant and economically large, especially when compared to the absence of any pre-investment gap.

The post-investment trajectory displays a clear J-curve pattern. Operating cash flow declines sharply in the years immediately following investment and begins to recover only after approximately five years. In contrast, non-US VC-backed startups exhibit substantially flatter post-investment dynamics.

The regression results in Table 2 confirm these patterns. Averaged over the post-investment period, operating cash flow is approximately 13 million SEK lower for US VC-backed startups relative to non-US VC-backed startups. Relative to the pre-investment mean, this corresponds to an effect size of roughly 120 percent, indicating that the magnitude of the decline is large compared to companies' baseline cash flow levels.

4.2 Sales

Panel B of Figure 1 presents analogous raw mean and event-time estimates for sales, measured in logarithms.[6] As with operating cash flow, pre-investment trends in sales are highly similar for startups that later receive US VC and non-US VC funding, with no evidence of differential pre-trends.

After investment, US VC-backed startups begin to outperform non-US VC-backed startups in terms of sales. The divergence emerges gradually and persists throughout the post-investment period. The

[6] To ensure a stable sample across the regressions for our different dependent variables, we replace missing sales log values (i.e., when absolute sales are 0) with 0s and include a "no sales" dummy as additional control variable. Results are stronger, both statistically and economically, when dropping missing sales log observations instead.

difference-in-differences estimates indicate that US VC-backed companies have higher sales following investment.

Table 2 shows that, averaged over the post-investment period, sales are approximately 0.5 log points higher for US VC-backed startups. This corresponds to 67% higher sales relative to non-US VC-backed companies. The effect is statistically significant at conventional levels and economically meaningful, indicating that deeper early losses among US VC-backed startups coincide with substantially higher future sales.

4.3 Venture capital funding

Panel C of Figure 1 displays raw means and event-time estimates for venture capital funding. Prior to investment, trends are similar across startups that later receive US VC and non-US VC funding. At the time of investment, however, US VC-backed companies receive substantially larger capital injections.

This funding gap persists and widens over time. US VC-backed startups continue to attract more venture capital in subsequent years, indicating sustained access to follow-on financing. Table 2 quantifies this difference: VC funding is approximately 130 percent higher for US VC-backed companies relative to non-US VC-backed companies in the post-investment period.

4.4 Summary and interpretation

Taken together, the baseline results establish three key facts. First, startups backed by US VCs exhibit significantly deeper J-curves in operating cash flow than those backed by non-US investors, with economically large and statistically significant declines that persist for several years. Second, these deeper early losses coincide with substantially higher sales in the post-investment period. Third, US VC-backed startups receive markedly more venture capital funding, both at the time of the initial investment and in subsequent years.

These patterns suggest that US VCs are associated with strategies that involve negative operating cash flows while scaling sales, supported by greater access to capital. Importantly, the absence of differential pre-trends across outcomes strengthens the interpretation that the post-investment divergence is consistent with changes associated with investor type rather than pre-existing startup differences. In the next section, we explore heterogeneity by investor characteristics to assess whether financing capacity can account for the observed patterns.

5 Financing capacity and J-curves

This section explores potential mechanisms underlying the deeper J-curves associated with US venture capital investments. We leverage the concept of financing risk (Nanda and Rhodes-Kropf 2013, 2017), and focus on financing capacity, i.e., investors' ability to provide follow-on funding either from their own assets under management, or through better access to later-stage investors.

5.1 Investor characteristics

We begin by documenting systematic differences in investor characteristics between US VCs and non-US VCs prior to investment. Table 3 reports these differences, focusing on VC firm and syndicate characteristics measured in the year before the focal investment.

Panel A of Table 3 presents differences in characteristics at the VC syndicate level, measured one year prior to investment. These results mirror the company-level descriptive statistics in Table 1, but shift the focus from portfolio companies to investor attributes.

The most pronounced difference concerns VC firm size. US VC syndicates manage substantially more capital than non-US VC syndicates. Assets under management are higher by approximately 37.3 billion SEK, and the difference is statistically significant. This gap is economically large and indicates markedly greater internal financing capacity among US VC investors.

US VCs are also more experienced in terms of investment activity. Syndicates involving US VCs have funded roughly 60 more startups prior to the focal investment, corresponding to an average of approximately 166 funded startups for US VCs compared to 107 for non-US VCs. This difference is statistically significant and suggests greater breadth of prior investment experience.

In contrast, differences in measured VC performance are smaller but still meaningful. Performance is measured as the fraction of funded startups that achieve an exit, defined as an IPO or acquisition. In the overall sample, US VCs exhibit an exit rate of approximately 24 percent, compared to about 16 percent for non-US VCs, implying a difference of roughly 8 percentage points. This difference is statistically significant and indicates that US VCs are not only larger but also more successful on average by this metric.

Panel B of Table 3 disaggregates these results to the VC–company level, treating each VC firm–portfolio company observation as a separate data point. The qualitative patterns remain unchanged. Differences in assets under management remain large and statistically significant, while differences in the number of previously funded startups and in exit performance attenuate somewhat but remain positive.

Finally, Panel C restricts attention to startups that receive US VC funding and compares US VC and non-US VC investors within the same investment syndicate. This within-syndicate comparison is particularly informative, as it holds constant the target company and investment opportunity. Even within these syndicates, US VCs are substantially larger than their non-US VC co-investors. Assets under management are higher by approximately 32 billion SEK, and US VCs have funded significantly more startups prior to the investment. Differences in performance measures persist as well, though they are smaller in magnitude. Overall, Panel C implies that the differences between US VC and non-US VC syndicates in Panel A are indeed driven by US VC firms.

Taken together, Table 3 documents large and systematic differences in size, experience, and performance between US VCs and non-US VCs. These differences are present both across syndicates and within the same syndicates investing in the same startups, highlighting that US VCs bring distinct financial and organizational resources to their portfolio companies.

5.2 VC firm size and access to internal capital

We next examine whether financing capacity is related to the depth of post-investment J-curves. The central prediction is that if access to capital drives the deeper J-curves associated with US VC investments, then these differences should disappear among large VC firms, for which financing constraints are less likely to bind.

To assess this prediction, we split the sample into investments by large and small VC firms based on assets under management. Figures 2 and 3 replicate the baseline event-time analysis separately for these subsamples. As in Figure 1, Panel A reports cash from operations, Panel B reports sales, and Panel C reports VC funding both in raw means and as event-time estimates.

Figure 2 presents the results for the large VC firm subsample. Across all three outcomes, startups backed by US VCs and non-US VCs exhibit parallel trends prior to investment, with no evidence of strong differential pre-trends. Importantly, unlike in the baseline sample, there are also no economically meaningful differences in post-investment dynamics. The sharp J-curve pattern in operating cash flow documented in Figure 1 disappears entirely. Similarly, there are no differential post-investment sales between US VC- and non-US VC-backed companies, and scaling patterns are indistinguishable across investor types.

These graphical patterns are confirmed by the regression estimates reported in Table 4. In the large VC firm subsample, the post-investment coefficients for operating cash flow and sales are small in magnitude and statistically insignificant. While US VC-backed startups continue to receive somewhat more VC funding even among large investors, the magnitude of this difference is substantially smaller than in the full sample and does not translate into differential scaling or operating performance.

Taken together, the results for large VC firms are consistent with the view that when financing constraints are unlikely to bind, US VC and non-US VC investors generate similar post-investment dynamics.

Figure 3 reports the corresponding results for the small VC firm subsample. This subsample includes VC firms with low reported assets under management as well as firms for which asset data are missing. As a result, it predominantly captures smaller investors, although we cannot rule out that some large VC firms are included due to missing data.

In this subsample, we observe the emergence of a delayed J-curve pattern following US VC investments. Operating cash flow initially remains flat relative to non-US VC-backed startups, but begins to decline and then recover approximately three years after the initial investment. This delayed pattern is mirrored in sales and VC funding, both of which start to increase around the same time. Compared to the baseline results, the J-curve is shifted forward in event time rather than absent.

These dynamics suggest that the J-curve patterns associated with smaller US VCs emerge only after a delay. A natural interpretation is that smaller US VCs initially face tighter financing constraints and subsequently rely on additional capital inflows, potentially from larger co-investors, to support scaling. We return to this interpretation in the analysis of investor networks below.

Overall, the heterogeneity by VC size provides consistent evidence that financing capacity is an important determinant of the depth and timing of post-investment J-curves. When investors are sufficiently large, differences between US VCs and non-US VCs largely vanish. When investors are smaller, J-curves re-emerge but with a delay. This pattern suggests that smaller US VCs have better access to later-stage investors. The next section investigates this more closely.

5.3 VC networks and access to external capital

We next examine whether access to external capital through investor networks contributes to differences in the depth of J-curves. Even when VC firms do not have sufficient internal capital to support aggressive scaling, strong networks may allow them to mitigate financing constraints by attracting new investors. If networks matter, we should observe greater entry of new investors following US VC investments, particularly among smaller US VCs for which internal financing capacity is more limited.

Figure 4 examines the entry of new investors following VC investment. Panel A shows the total number of new investors by event time. After investment, startups backed by US VCs attract substantially more new investors than those backed by non-US VCs. The divergence emerges gradually and persists throughout the post-investment period.

Panel B of Figure 4 splits this analysis by VC size. Among large VC firms, the difference in investor entry between US VCs and non-US VCs is present but relatively modest. In contrast, among small VC firms, the number of new investors following US VC investments rises sharply, particularly after event time three. This timing coincides closely with the delayed J-curve observed for small US VCs in Figure 3.

The regression results in Table 5 confirm these patterns. In the full sample, US VC investments are associated with a 134 percent increase in the number of new investors entering after the initial investment, relative to non-US VC investments. In the large VC firm subsample, the effect remains statistically significant but is substantially smaller, at approximately 75 percent. In contrast, in the small VC firm subsample, the increase in new investors is approximately 107 percent. These estimates are statistically significant and economically large, indicating that networks play a particularly important role for smaller US VCs.

To further understand the sources of these new investors, Figure 5 distinguishes between investors originating from within and outside the initial syndicate's network. Panel A shows that small US VC-backed startups experience a marked inflow of large new investors beginning around event time four.

This timing again aligns closely with the onset of the delayed J-curve in operating cash flow and sales for this group.

Panels B and C show that while US VC-backed startups attract somewhat more new investors from within the initial syndicate's network, the dominant difference arises from investors entering from outside the original network. Relative to non-US VCs, US VCs are substantially more successful at pulling in new external investors, rather than merely expanding within existing syndication relationships.

Taken together, these results suggest that networks appear to facilitate access to external capital. When internal capital is limited, access to external capital through networks appears to be associated with more aggressive scaling among US VC-backed companies. The close alignment between the timing of new investor entry and the emergence of J-curves in the small VC subsample provides further support for a financing-based interpretation.

5.4 Summary and interpretation

Overall, the evidence on VC size and networks points to financing capacity as a plausible mechanism behind the observed pattern that US VC-backed startups sustain deeper early losses.

It is important to note, however, that mechanism analyses in this section rely on stronger identifying assumptions than the baseline results. In particular, heterogeneity by VC size and network characteristics assumes that, conditional on controls and fixed effects, the assignment of startups to US VCs versus non-US VCs is comparable within each subsample. If unobserved company characteristics differentially sort into US VCs within size or network groups, the estimated differences may partially reflect selection rather than financing capacity.

A related concern is that splitting the sample reduces statistical power and, in the case of missing assets-under-management data, may introduce classification error. Additionally, a smaller sample amplifies the influence of outliers, particularly in later event years.

As a result, the analyses in this section should not be interpreted as causal estimates of the effect of size or networks per se. Instead, they provide structured descriptive evidence on how post-investment dynamics vary with investor characteristics that plausibly proxy for financing capacity.

6 Additional analyses and robustness

This section presents additional analyses designed to assess the robustness of the baseline results and to evaluate alternative explanations. We focus on whether the deeper J-curves associated with US venture capital investments can be explained by exposure to US investors, investor experience or performance. We also consider alternative dependent variables and alternative definitions of treatment. Finally, we report further robustness checks related to selection and attrition.

6.1 US exposure

One possible alternative mechanism behind the deeper J-curves associated with US venture capital investors is exposure to US investment practices rather than investor type per se. In this subsection, we examine whether experience with US investors or exposure through US limited partners can account for the baseline results.

We first study whether prior syndication with US VCs affects post-investment dynamics among non-US investors. The underlying hypothesis is that non-US VCs may learn US-style scaling strategies through co-investment with US investors. To investigate this possibility, Figure 6 reports event-time estimates for operating cash flow (Panel A), sales (Panel B), and venture capital funding (Panel C) within a sample of startups backed by non-US VCs only. We split this sample into treatment and control according to whether the non-US VC had previously co-invested with a US VC. Figure 6 shows no strong differential pre-trends across operating cashflow and sales. Importantly, there are also no meaningful differences in post-investment dynamics between startups backed by non-US VCs with prior US syndication experience and those without such experience. We do not observe deeper J-curves in operating cash flow, nor do we see faster scaling in sales or sustained differences in venture capital funding. The only discernible difference is a modest increase in investment at the time of the initial financing round, which does not persist over time. This increase is also coupled with a statistically significant difference in the pre-period. The corresponding regression results are reported in Table 7, and Table IA.1 describes the sample. Panel A shows that prior US syndication experience is not associated with statistically or economically significant differences in operating cash flow or sales in the post-investment period. These results provide little support for a learning or imitation mechanism operating through prior syndication with US investors.[7]

We next examine whether exposure to US limited partners is correlated with post-investment dynamics by manually collecting additional data on limited partners from CapitalIQ and Preqin. The motivation for this analysis is that LP composition may affect contracting or monitoring, potentially shaping VC firms' strategic choices to operate with negative operating cash flows to drive faster growth. To isolate this channel, we restrict attention to startups that never receive US VC funding and compare outcomes of non-US VCs with US LPs, to those without US LPs. Table IA.4 describes the sample, and Figure 7 presents event-time estimates for this comparison. A key challenge in interpreting these results is that the presence of a US LP is positively correlated with VC firm size, with 50% of large and only 6% of small non-US VC firms having a US LP (correlation of 0.36). As a result, sample sizes are small, and it is difficult to disentangle the effect of LP composition from the effect of investor scale. The results in Figure 7 should therefore be interpreted as capturing a combination of VC size and LP exposure rather than a clean LP effect. With this caveat in mind, Figure 7 shows weak evidence of a J-curve and modestly higher growth among companies backed by non-US VCs with US LPs, although the patterns are less pronounced than in the baseline US VC analysis. The regression estimates in Table 8 corroborate this interpretation. Panel A shows that operating cash flow is on average 7.5 million SEK lower in the post-investment period, corresponding to a 183 percent decline relative to pre-investment levels. There is no statistically significant effect on sales, while venture capital funding is approximately 60 percent higher for non-US VCs with US LPs.

To disentangle the investor size and US LP mechanisms, we repeat the analysis in a refined sample that explicitly accounts for investor size. Like before, we construct a sample of startups that never receive US VC funding and compare outcomes of non-US VCs with US LPs, to those without US LPs. However, we explicitly control for investor size by additionally matching on a dummy equal to one if a startup is backed by a large investor, which we define as a non-US VC firm with AUM above the median AUM of US VC firms. This allows us to test whether investments by non-US VCs with US LPs are associated with deeper J-curves over and above investor size effects. Table IA.5 describes the sample, and Figure 8

[7] A further conjecture is that the exposure to US investors only changes when the syndicated investments turn into success. We therefore rerun this analysis, redefining treatment as prior syndication experience with a US VC in a startup that eventually achieved an exit. Again, we find that even this refined definition of US exposure does not generate J-curve patterns (Figure IA.1, Table IA.2, and Table IA.3).

presents event-time estimates for this comparison. The J-curve patterns are even less pronounced, both in economic magnitude and statistical significance. The regression estimates in Table 9 reinforce this interpretation. There is no statistically significant effect on operating cash flow and sales, while venture capital funding is approximately 45 percent higher for non-US VCs with US LPs.

Overall, these results suggest that US LP exposure may be associated with greater capacity to finance early losses. However, given the strong correlation between US LP presence and VC firm size, our interpretation is that these effects primarily reflect differences in financing capacity rather than a distinct role of LP composition.

6.2 Experience and performance

We next examine whether differences in VC firm experience or past performance can explain the deeper J-curves and faster scaling associated with US venture capital investors. A natural alternative mechanism is that US VCs may simply be more experienced or more successful, and that these characteristics, rather than financing capacity, drive the baseline results.

We first condition on VC firm experience. Specifically, we restrict the sample to investments made by experienced VC firms, which we define as above-median number of funded startups.[8] This construction ensures that both US and non-US VCs in the subsample have substantial prior investment experience. Figure IA.2 reports event-time estimates for operating cash flow (Panel A), sales (Panel B), and venture capital funding (Panel C) within this experienced VC subsample. The patterns closely mirror the baseline results. Startups backed by US VCs exhibit a pronounced J-curve in operating cash flow, alongside higher post-investment sales and substantially greater venture capital funding. Pre-investment trends remain parallel across US and non-US VC investments. The corresponding regression estimates are reported in Table IA.6. In the experienced VC subsample, US VC investments are associated with operating cash flow that is approximately 144 percent lower in the post-investment period, sales that are roughly 80 percent higher, and venture capital funding that is approximately 137 percent higher, relative to non-US VC investments. All effects are economically large and statistically significant. These results indicate that conditioning on VC firm experience does not attenuate the baseline US VC effect.

[8] In unreported tests we confirm that results are similar when using the number of investments as alternative measure for experience.

We next condition on prior VC firm performance. We restrict the sample to VC firms with above-median past performance, measured as the fraction of previously funded startups that achieved an exit through an IPO or acquisition. This subsample focuses on VCs with demonstrated success in prior investments. Figure IA.3 presents the corresponding event-time estimates. As in the experienced subsample, startups backed by US VCs continue to display deeper J-curves in operating cash flow, higher sales, and greater access to venture capital funding. There is no evidence that conditioning on past success eliminates or meaningfully weakens the baseline patterns. Table IA.6 confirms these findings. In the successful VC subsample, US VC investments are associated with operating cash flow that is approximately 70 percent lower and venture capital funding that is roughly 133 percent higher in the post-investment period. The sales effects are positive but less precisely estimated.

Taken together, these results suggest that neither VC firm experience nor prior investment success is sufficient to explain the deeper J-curves and faster scaling associated with US VC investments. Even when comparing US and non-US VCs with similar levels of experience or past performance, the baseline patterns persist. This evidence points away from explanations based solely on superior know-how or selection on successful investors and is instead consistent with mechanisms related to financing capacity, as emphasized in Section 5.

6.3 Burn rate and runway

We next assess the robustness of our findings to alternative ways of measuring J-curves and startup scaling. The objective is twofold: first, to provide a complementary cross-sectional characterization of J-curves using summary measures of burn rate and runway as well as depth and width; and second, to verify that the baseline patterns are not specific to operating cash flow and sales as the outcome variable.

We begin by constructing alternative measures of J-curves at the company level. Using information from the post-investment period, we define two sets of summary statistics: Burn rate and runway as well as J-curve depth and J-curve width. Runway is defined as the number of post-period years until a company's next VC round. Burn rate is defined as the average annual cash used by a company during the post-period, calculated as $\frac{CashBalance_{t-1}+Funding_t}{Runway_t}$. These two measures pertain to the focal investment round.

We further consider two measures of the overall shape of J-curves. Depth is defined as the maximum decline in operating cash flow relative to the year prior to investment ($t = -1$), while width is defined as the number of post-investment years it takes for operating cash flow to return to its $t = -1$ level.

These measures are constructed using only post-investment data but are analyzed in a cross-sectional regression framework at the company level, keeping only observations measured at $t = 0$. This approach provides a complementary perspective to the event-time analysis by summarizing the shape of the J-curve using forward-looking outcomes.

Table IA.16 reports the results on burn rate and runway. Startups backed by US venture capital investors have higher annual cash usage and raise additional VC funding more quickly. Specifically, their annual "burn" is approximately 27 million SEK higher relative to non-US VC-backed startups. US VC-backed startups also raise their next funding round about 1.4 years earlier.

Table IA.17 reports the results on J-curve depth and width. Startups backed by US venture capital investors exhibit substantially deeper J-curves. The estimated depth is approximately 26 million SEK larger in absolute value, indicating significantly greater maximum losses relative to non-US VC-backed companies. At the same time, the width of the J-curve is longer: US VC-backed startups take on average roughly 0.7 additional years to return to their pre-investment operating cash flow level.[9]

Overall, these analyses confirm the baseline findings using a different empirical design: US VC investments are associated with higher burn rates and shorter runways as well as both deeper and more persistent J-curves.

6.4 Alternative dependent variables

Next, to corroborate and expand our base results, we reestimate our baseline event-time framework using alternative dependent variables. First, we replace operating cash flow with EBITDA as a measure of operating performance. Second, we capture company scaling through the expansion of foreign subsidiaries, which reflects international scaling and growth rather than revenue increases alone. Third, we examine exits and follow-on financing rounds as alternative measures of investment outcomes and scaling activity. Figure IA.9 presents the corresponding event-time estimates, and Table IA.18 reports the regression

[9] A practical challenge in measuring runway and width is right-censoring at the end of the sample period. For startups without a follow-on round during our post period or whose operating cash flow has not returned to its $t = -1$ level by the end of our post period, we assign a runway or width of nine years (i.e., one year after our post period). This convention ensures that all startups are included while preserving the ordinal interpretation of the runway and width measures. The results are robust to alternative treatments of right-censoring.

results. Across all alternative outcomes, the qualitative patterns remain unchanged. Using EBITDA, we continue to observe pronounced J-curves for US VC-backed startups. Using foreign subsidiaries as an outcome, US VC-backed startups expand more rapidly abroad in the post-investment period. Similarly, US VC-backed companies are more likely to raise follow-on rounds and to achieve exit events. Unconditionally, US VC backed startups are not only more likely to exit successfully (35% vs 30%), but also to have larger observed exit values (USD 246 million vs USD 128 million). Taken together, these results indicate that the baseline findings are not sensitive to the choice of outcome variable. Deeper early losses and faster scaling among US VC-backed startups are evident across multiple measures of operating performance, growth, and financing activity.

6.5 Robustness through redefining treatment

In this subsection, we assess whether the baseline results are driven by US VC status per se or by other investor characteristics correlated with US investors, such as size, experience, performance, or foreign origin. To do so, we redefine the treatment variable while explicitly excluding all startups that ever receive US VC funding. This restriction ensures that the estimated effects are not mechanically driven by US investors.

The empirical design proceeds as follows. We begin with a sample of companies that receive venture capital financing but never receive US VC investment. Within this sample, we redefine treatment as the first investment by: (i) a large VC firm, (ii) an experienced VC firm, (iii) a successful VC firm, or (iv) a foreign VC firm. For each definition, we re-estimate the matching procedure and event-time specifications using the corresponding treatment indicator. The resulting analyses allow us to evaluate which investor characteristics generate J-curves and scaling patterns similar to those observed for US VC investments.

We first redefine treatment as the first investment by a large VC firm, measured by assets under management.[10] Figure IA.4 reports event-time estimates for operating cash flow, sales, and venture capital funding, and Table IA.8 reports the corresponding regression results. The balancing statistics in

[10]We use median values of US VC firm characteristics as cutoffs and classify missing VC firm characteristics as small/inexperienced/unsuccessful. Hence, our alternative treatment variables are conservative measures capturing “known” VC characteristics. Misclassifications of VC firms due to missing data would bias us against finding results. For instance, we classify a VC firm with missing assets under management as small, even though it might actually be large.

Table IA.7 show no economically meaningful differences in observable startup characteristics prior to treatment, indicating that the matching procedure performs well. The results show a muted but clearly discernible drop in operating cash flow following the first large VC investment. In the post-investment period, operating cash flow is approximately 17 million SEK lower, corresponding to a 167 percent decline relative to pre-investment levels. At the same time, companies exhibit substantially faster scaling: sales are approximately 210 percent higher, and venture capital funding is roughly 136 percent higher. These patterns closely resemble the baseline results for US VC investments, albeit with somewhat smaller magnitudes.

We also provide supporting evidence that larger VC firms are more able to provide internal follow-on funding. Specifically, we regress the number of reinvestments by $t = 0$ investors on the first large VC firm investment treatment dummy in the never US VC subsample, using only post-period observations. Results in Figure IA.5 and Table IA.9 show that large VC investors are relatively more likely to reinvest following their initial investment relative to small VC firms, which supports the notion that large VC firms internalize financing risk to a higher degree compared to small VC investors.

Next, we redefine treatment as the first investment by an experienced VC firm, defined as above-median number of previously funded startups. The balancing results in Table IA.10 indicate good balance across observable characteristics prior to treatment. Figure IA.6 and Table IA.11 show no evidence of J-curves or accelerated scaling following the first experienced VC investment. The estimated effects on operating cash flow and sales are small and statistically insignificant. Venture capital funding increases modestly, by approximately 16 percent, but this effect is substantially smaller than in the baseline analysis and does not translate into differential operating performance.

We then redefine treatment as the first investment by a successful VC firm, measured as being above the median in prior exit rates of funded startups. As shown in Table IA.12, companies are well balanced on observable characteristics prior to treatment. The event-time estimates in Figure IA.7 and the regression results in Table IA.13 show no evidence of J-curves in operating cash flow and no significant effects on sales. Venture capital funding increases following the first successful VC investment, but the magnitude is smaller than in the large-VC treatment and does not generate the characteristic J-curve pattern observed in the baseline results.

Finally, we consider treatment defined as the first investment by a foreign (non-US) VC firm. Table

IA.14 shows that treated and control startups are generally well balanced prior to treatment, although companies receiving foreign VC investments are slightly more likely to have foreign subsidiaries. Figure IA.8 and Table IA.15 show no clear J-curve in operating cash flow following the first foreign VC investment. While sales increase by approximately 100 percent and venture capital funding is around 36 percent higher, these effects are not accompanied by deeper early losses and are therefore distinct from the baseline US VC patterns.

Taken together, these analyses indicate that investor size is the characteristic most closely associated with the J-curve and scaling patterns documented in the baseline results. Redefining treatment based on experience, past performance, or foreign status does not reproduce the combination of deep early losses and rapid scaling observed for US VC investments. In contrast, redefining treatment based on VC firm size generates post-investment dynamics that closely resemble the baseline findings, consistent with financing capacity playing a central role.

6.6 Further robustness and discussion

This subsection reports additional robustness checks addressing concerns related to attrition and investor–entrepreneur matching.

First, a potential concern is that the baseline results may be driven by differential attrition from the sample in the post-investment period. If startups backed by US VCs exit the sample at different rates than those backed by non-US VCs, and if this attrition is correlated with startup outcomes, the estimated post-investment dynamics could be biased.

To assess this possibility, we implement a placebo-style attrition test. Specifically, we re-estimate the event-time difference-in-differences specifications using as outcomes the values of operating cash flow, sales, and venture capital funding measured in the year prior to investment ($t = -1$). Intuitively, if differential attrition were driving the baseline results, we would expect to observe spurious post-investment effects when using pre-investment outcomes, reflecting selective exit from the sample rather than genuine changes in company performance. Figure IA.10 reports the results of this exercise. Across all three outcomes, the estimated coefficients are flat and statistically insignificant throughout the post-investment period. We find no evidence of systematic divergence between US VC-backed and non-US VC-backed startups when pre-investment outcomes are used as dependent variables. These results suggest that differential attrition is unlikely to be driving the baseline J-curve and scaling patterns.

Second, a concern could be that the results may reflect matching between investors and entrepreneurs rather than the effect of investor characteristics on startup dynamics. For example, US VCs may systematically select entrepreneurs with higher risk tolerance, different growth preferences, or business models that inherently involve deeper early losses. While such matching cannot be fully ruled out, several features of the analysis mitigate this concern. The absence of differential pre-trends across outcomes and the similarity in observables of managers and directors in the portfolio companies prior to investment suggests that startups backed by US and non-US VCs are similar prior to investment. Moreover, the persistence of the baseline results when conditioning on VC firm experience and past performance indicates that the patterns are not driven solely by selection into high-quality or high-ability investors. Additionally, the disappearance of US VC effects among large VC firms and their delayed emergence among small VC firms are difficult to reconcile with a pure matching explanation, as they imply that post-investment dynamics depend on investor financing capacity rather than fixed investor or entrepreneur traits.

7 Conclusion and policy discussion

This paper examines whether VC-backed startups exhibit systematic differences in their loss trajectories depending on the origin of their investors. Using detailed financial statement data on Swedish startups and a stacked difference-in-differences design around the first venture capital investment, we document that J-curves are a pervasive feature of VC-backed companies. More importantly, these J-curves are substantially deeper and more persistent for startups backed by US venture capital investors than for otherwise comparable companies backed by non-US investors. These deeper early losses coincide with faster scaling, reflected in higher long-run sales and substantially greater access to venture capital funding.

We further investigate why US venture capital investors are associated with deeper J-curves. Motivated by the idea that financing deep J-curves requires substantial and sustained access to capital, we examine heterogeneity across investor characteristics. Differences between US and non-US investors disappear among startups backed by large VC funds, suggesting that financing capacity plays a central role. Among smaller VC firms, however, US investors remain associated with deeper J-curves. This difference emerges with a delay that closely coincides with the entry of new, often large, follow-on investors, pointing to the importance of investor networks and access to later-stage capital markets.

Taken together, the evidence suggests that the deeper J-curves associated with US VC investors reflect greater financing capacity, arising both from larger fund size and from stronger access to follow-on investor networks. While our analyses cannot fully isolate causal effects of these channels, the consistency of the patterns across outcomes, subsamples, and specifications suggests that the ability to finance sustained periods of negative cash flow plays an important role in shaping startup growth trajectories.

These findings have implications for venture capital policy in Europe. A central objective of entrepreneurship and innovation policy is to support the growth of high-potential startups and to close perceived scale-up gaps relative to the United States. Our results suggest that financing capacity plays an important role in shaping startups' loss trajectories and growth dynamics.

First, policies that focus narrowly on increasing the number of VC-backed startups may be insufficient. Deep J-curves require the ability to sustain large and persistent early losses, which depends on access to substantial follow-on capital. Fragmented venture capital markets with many small funds may struggle to support aggressive scaling, even when investment expertise is present. Consistent with this, the European Innovation Council announced in 2025 that it was setting up the 'Scaleup Europe Fund,' a multi-billion strategic growth fund.[11]

Second, the results highlight the importance of follow-on financing and investor networks. Smaller investors can support scaling when they are embedded in networks that facilitate access to larger pools of capital. Policies that promote syndication across borders, reduce regulatory frictions to cross-country investment, or strengthen connections between domestic VCs and international investors may therefore expand financing capacity without requiring consolidation of the VC sector.[12]

Third, institutional investors and public capital providers may help mitigate financing constraints. To the extent that US VC markets benefit from larger fund sizes and more flexible access to capital, policies that encourage pension funds, insurance companies, and other long-horizon investors to participate in European VC markets may help replicate these conditions. Our results caution against interpreting early

[11] See https://eic.ec.europa.eu/eic-fund/scaleup-europe-fund_en accessed March 2026.

[12] See Bradley et al. (2019) for a detailed discussion of such policies.

operating losses as policy failures. Deeper J-curves may be a feature, rather than a flaw, of successful scale-up strategies.

More broadly, the findings underscore that scaling high-growth startups requires the capacity to finance sustained periods of negative cash flow. Policies aimed at closing the European scale-up gap should therefore place greater emphasis on financing depth and continuity, rather than solely on entry into venture capital markets.

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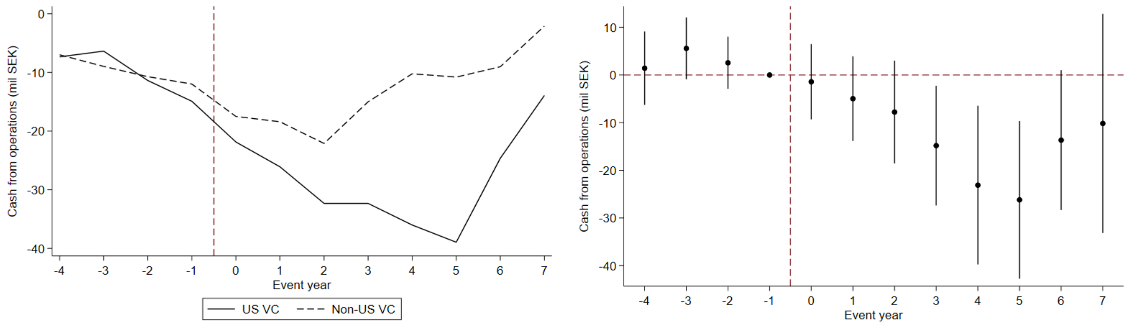
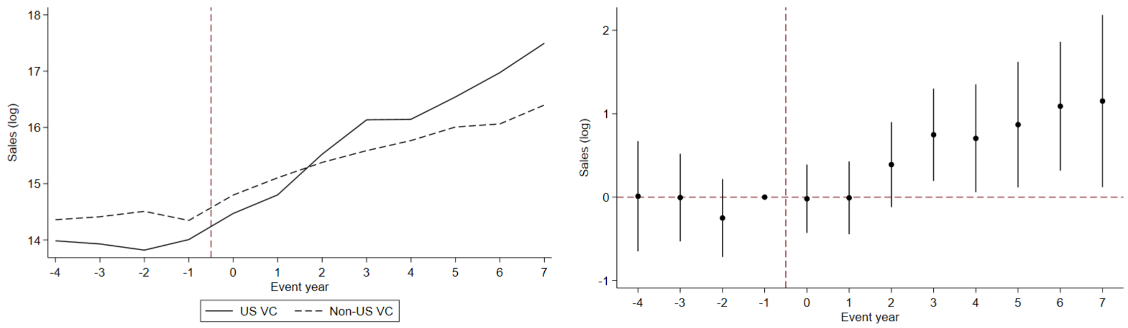
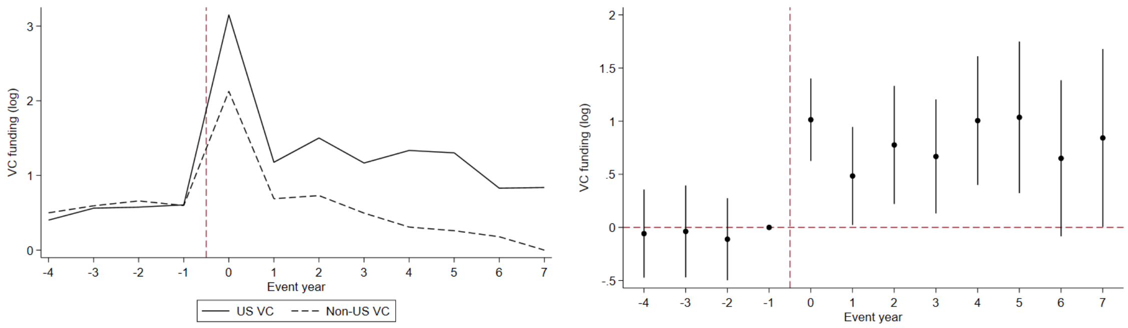


A: Cash from operations

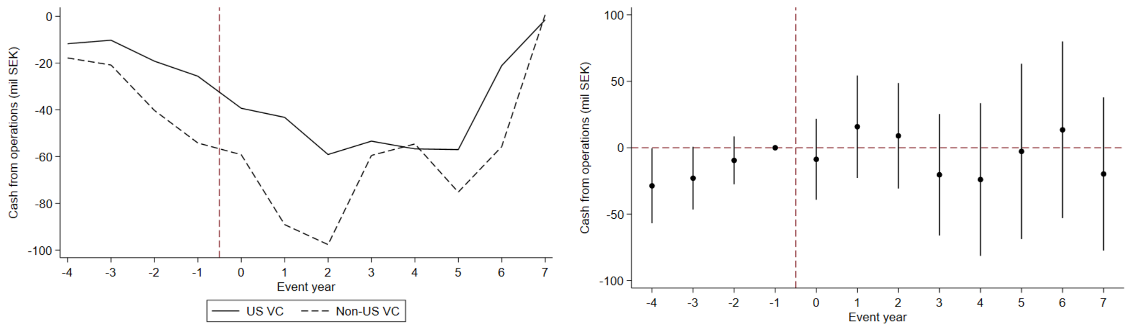


B: Sales

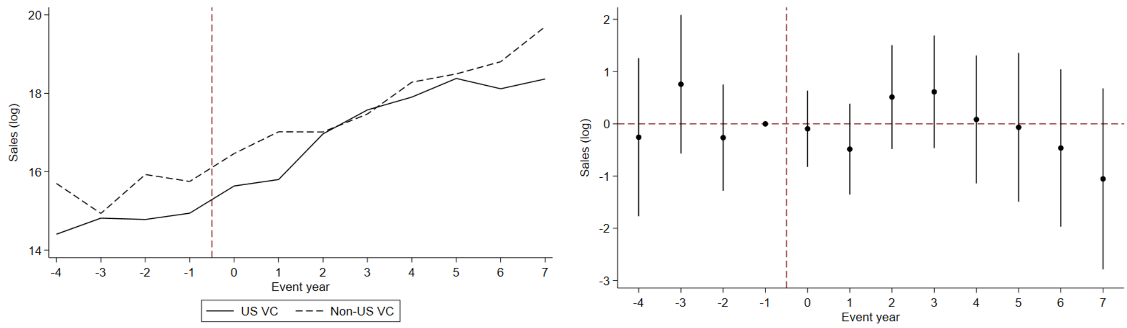


C: VC funding

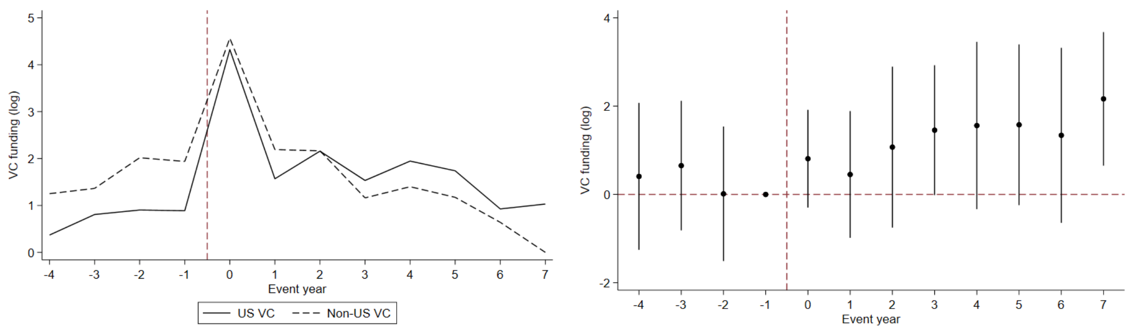
Figure 1. Outcomes around first US VC investment. This figure shows the effects of receiving initial US VC funding on cash from operations, sales, and VC funding. It displays the raw means for companies receiving their first US VC investment and those receiving funding from non-US VC investors (left) as well as DiD coefficients estimated by event time with 95% confidence intervals (right). Table 1 describes the sample and Table 2 shows the regression results underlying these event time figures.



A: Cash from operations

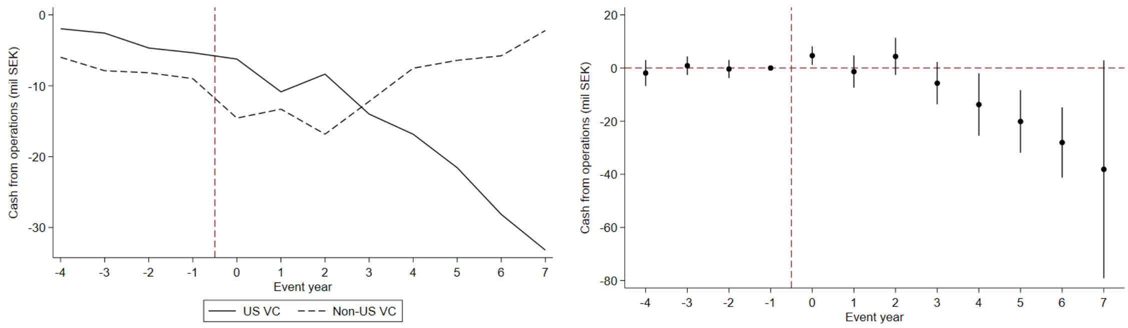


B: Sales

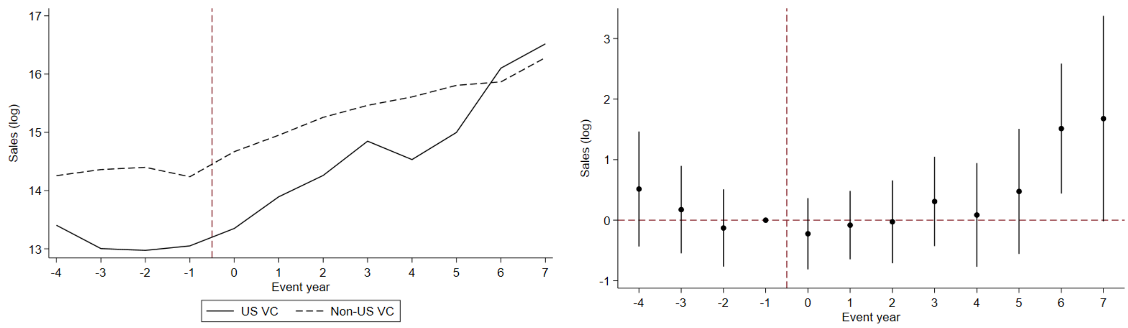


C: VC funding

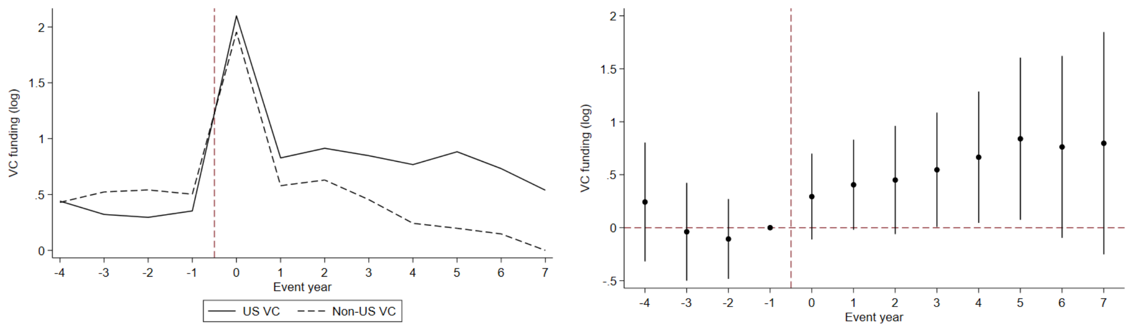
Figure 2. Outcomes around first US VC investment in large VC firm subsample. This figure shows the effects of receiving initial US VC funding on cash from operations, sales, and VC funding. It displays the raw means for companies receiving their first US VC investment and those receiving funding from non-US VC investors (left) as well as DiD coefficients estimated by event time with 95% confidence intervals (right). We define large VC as above median VC syndicate AUM, where syndicate AUM is the maximum value of VC firm AUM within a syndicate. Table 4 shows the regression results underlying these event time figures.



A: Cash from operations

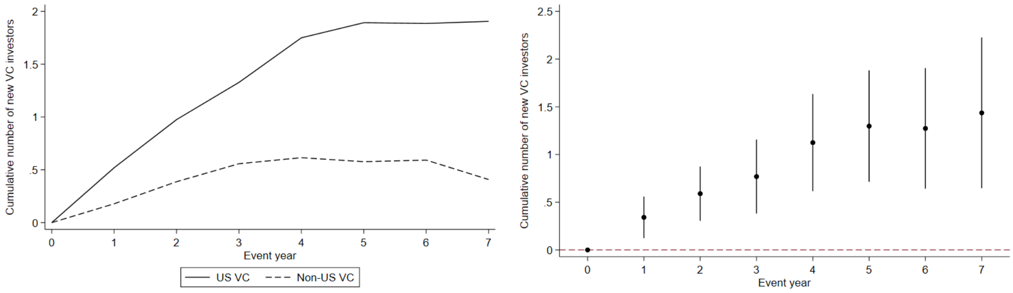


B: Sales

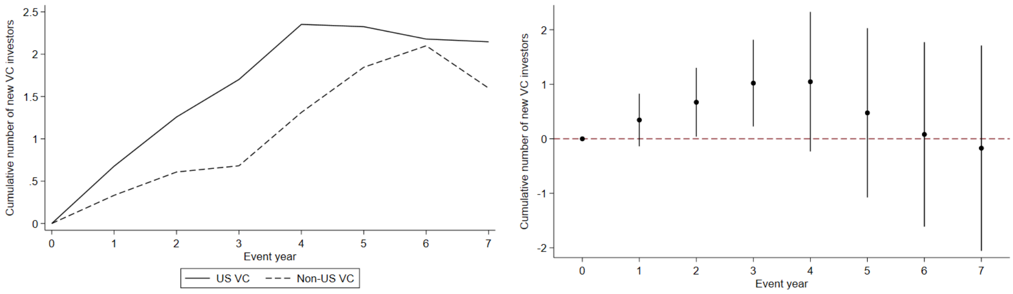


C: VC funding

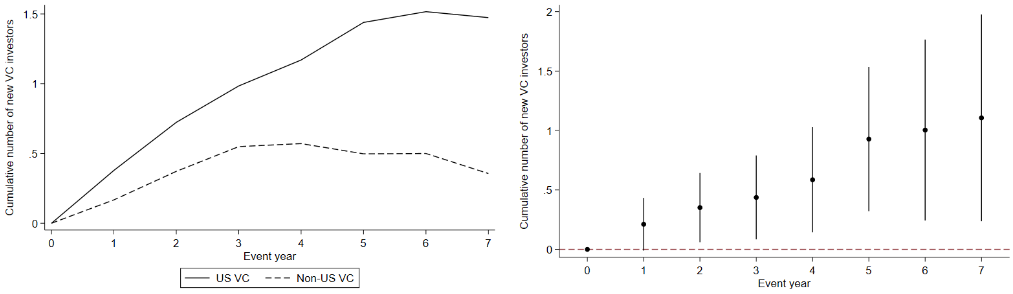
Figure 3. Outcomes around first US VC investment in small VC firm subsample. This figure shows the effects of receiving initial US VC funding on cash from operations, sales, and VC funding. It displays the raw means for companies receiving their first US VC investment and those receiving funding from non-US VC investors (left) as well as DiD coefficients estimated by event time with 95% confidence intervals (right). We define small VC as at or below median VC syndicate AUM, where syndicate AUM is the maximum value of VC firm AUM within a syndicate. Table 4 shows the regression results underlying these event time figures.



A: New investors after investments by VCs

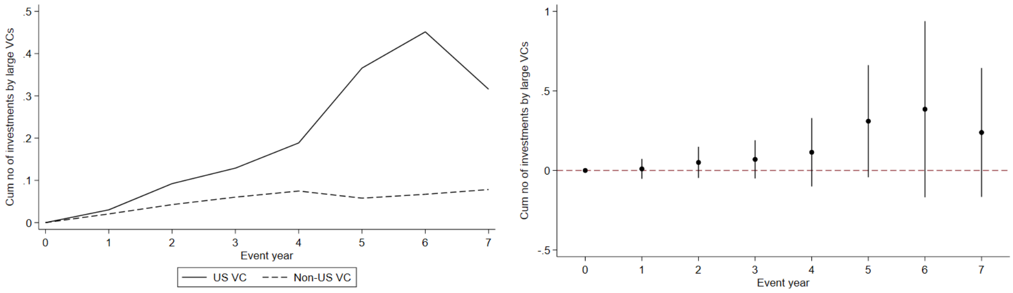


B: New investors after investments by large VCs

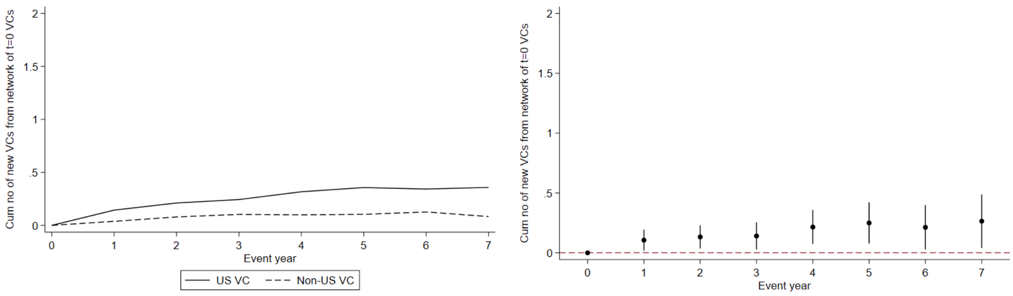


C: New investors after investments by small VCs

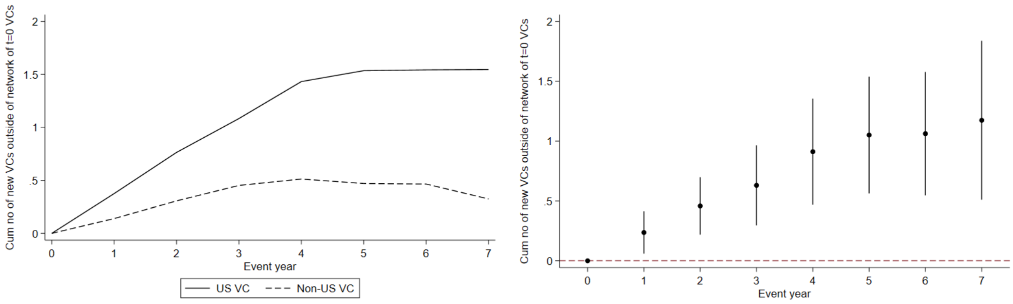
Figure 4. New investors after first US VC investment. This figure shows the effects of receiving initial US VC funding on networks (cumulative number of new investors). It displays the raw means for companies receiving their first US VC investment and those receiving funding from non-US VC investors (left) as well as event time regression coefficients from a regression run only in the post period with event year zero omitted and with 95% confidence intervals (right). Table 5 shows the regression results underlying these event time figures.



A: New *large* investors after investments by small VCs

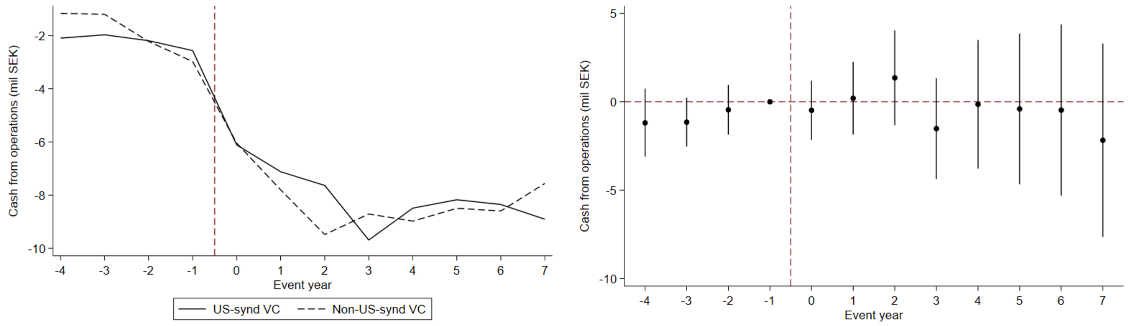


B: New investors from *inside* of $t = 0$ investors' networks

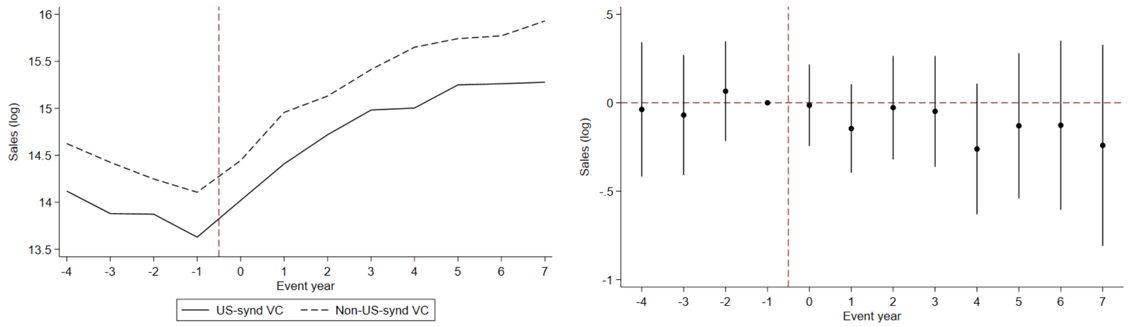


C: New investors from *outside* of $t = 0$ investors' networks

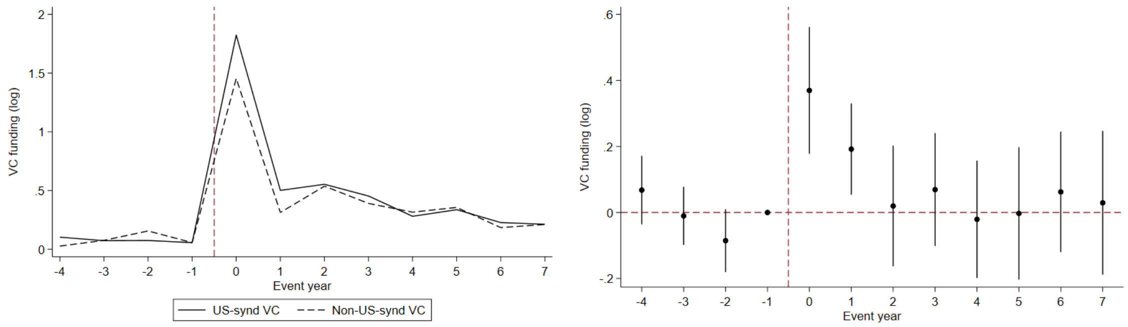
Figure 5. New investors from inside and outside of networks after first US VC investment. This figure shows the effects of receiving initial US VC funding on the cumulative number of new large investors as well as new investors from inside and outside of the networks of $t = 0$ investors. It displays the raw means for companies receiving their first US VC investment and those receiving funding from non-US VC investors (left) as well as event time regression coefficients from a regression run only in the post period with event year zero omitted and with 95% confidence intervals (right). Table 6 shows the regression results underlying these event time figures.



A: Cash from operations

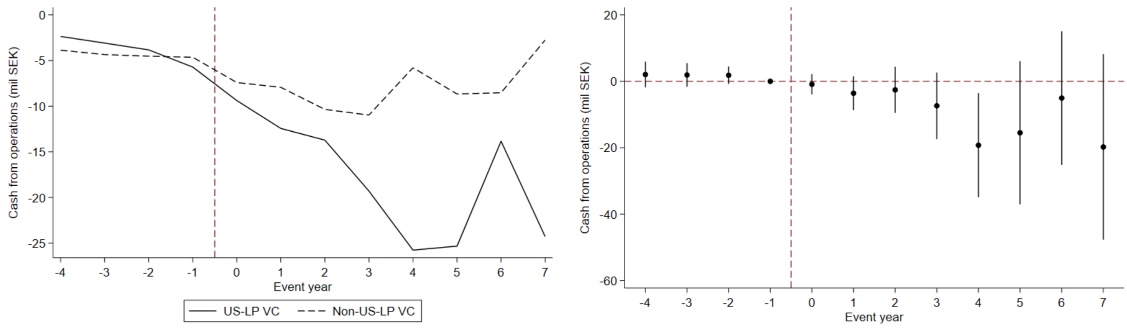


B: Sales

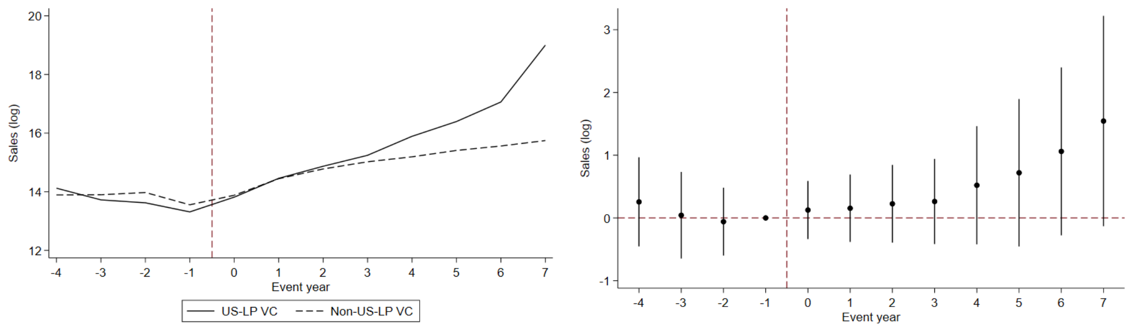


C: VC funding

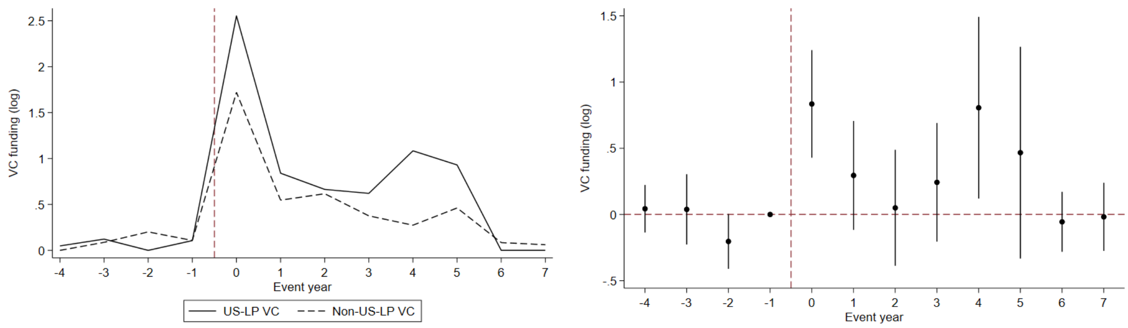
Figure 6. Outcomes around first US-syndicator VC investment in never-US VC subsample. This figure shows the effects of receiving initial US-syndicator VC funding on cash from operations, sales, and VC funding in the never-US VC subsample. We define initial US-syndicator as an investment by a non-US VC firm that has previously co-invested with a US VC. It displays the raw means for companies receiving their first US-synd VC investment and those receiving funding from non-US-synd VC investors (left) as well as DiD coefficients estimated by event time with 95% confidence intervals (right). Table IA.1 describes the sample and Table 7 shows the regression results underlying these event time figures.



A: Cash from operations

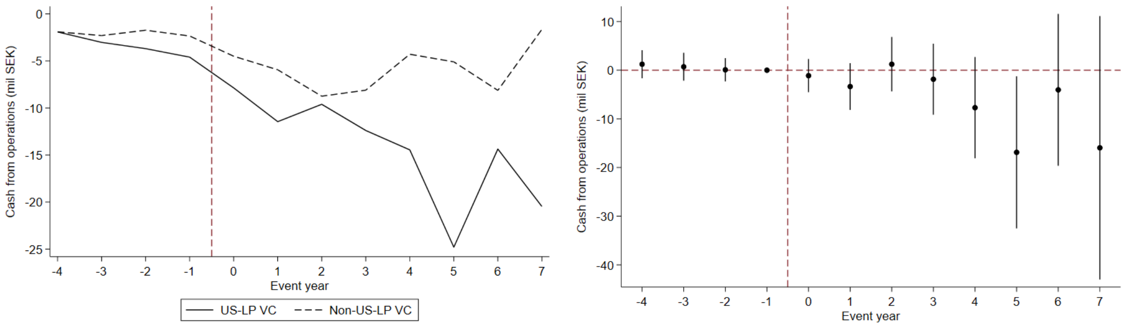


B: Sales

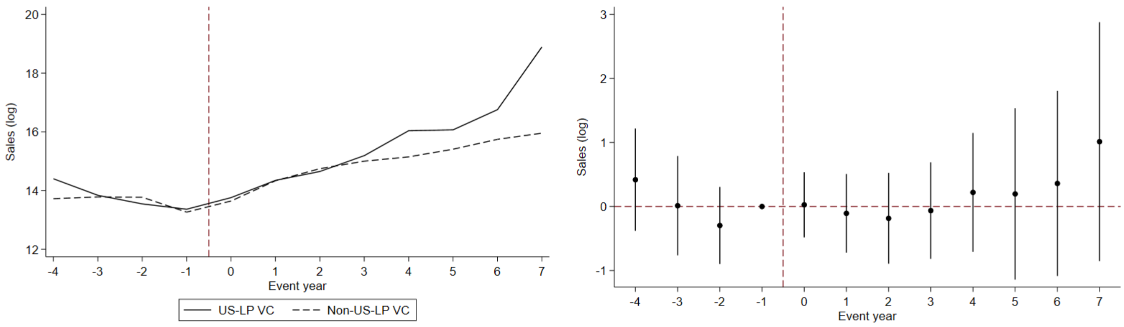


C: VC funding

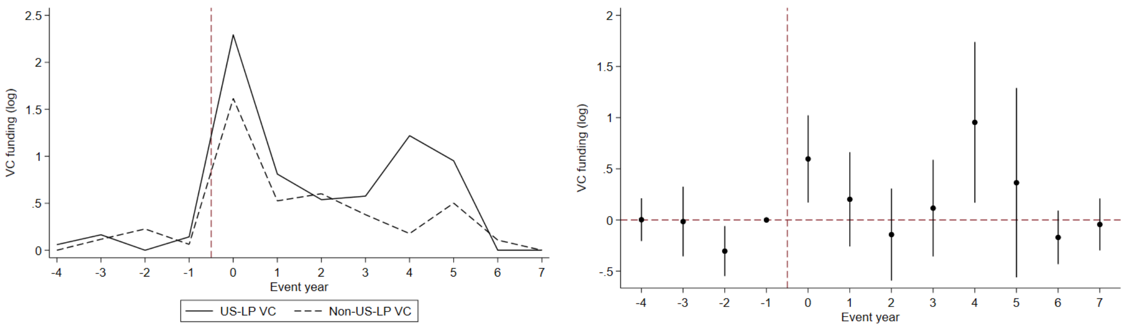
Figure 7. Outcomes around first US-LP VC investment in never-US VC subsample. This figure shows the effects of receiving initial US-LP VC funding on cash from operations, sales, and VC funding in the never-US VC subsample. We define initial US-LP as an investment by a non-US VC firm that has a limited partner from the US. It displays the raw means for companies receiving their first US-LP VC investment and those receiving funding from non-US-LP VC investors (left) as well as DiD coefficients estimated by event time with 95% confidence intervals (right). Table IA.4 describes the sample and Table 8 shows the regression results underlying these event time figures.



A: Cash from operations



B: Sales



C: VC funding

Figure 8. Outcomes around first US-LP VC investment in never-US VC subsample with matching on investor size. This figure shows the effects of receiving initial US-LP VC funding on cash from operations, sales, and VC funding in the never-US VC subsample with matching on investor size. Specifically, we include a dummy equal to one if a startup is backed by a large investor, which we define as a non-US VC firm with AUM above the median AUM of US VC firms, as an additional matching variable. We define initial US-LP as an investment by a non-US VC firm that has a limited partner from the US. It displays the raw means for companies receiving their first US-LP VC investment and those receiving funding from non-US-LP VC investors (left) as well as DiD coefficients estimated by event time with 95% confidence intervals (right). Table IA.5 describes the sample and Table 9 shows the regression results underlying these event time figures.

Table 1
Descriptive statistics

This table presents descriptive statistics by comparing companies receiving their first US VC investment and those receiving funding from non-US VC investors a year before the funding round. We require companies to have been in operation for at least one year prior to the funding round. EBITDA, operating cash, sales, VC round amount, and assets are in millions of real 2025 Swedish krona (SEK). Average Euro and US dollar to SEK exchange rates for December 2025 are 10.895 and 9.294, respectively. When constructing our matched sample, we match jointly on industry (3 bins), stage (3 bins), EBITDA at $t-1$ (quartiles), and number of employees at $t-1$ (quartiles). Section 3 describes the sample construction process in more detail. Panel A shows continuous versions of the variables used for the matching, except for industry. A χ^2-test for differences in the distribution of companies receiving initial US VC and non-US VC funding across industries (using all levels) at $t-1$ is insignificant with a p-value of 0.690. Panel B shows variables used in the analysis but not for the matching, and Panel C shows other variables.

	(1) Full	(2) US VC	(3) Non-US VC	(4) Difference	(5) *t*-statistic
Panel A: Variables used for matching					
EBITDA (mil SEK)	-13.043	-14.036	-12.702	-1.334	(-0.455)
Employees	15.734	17.554	15.109	2.445	(0.598)
VC round number	0.683	0.672	0.687	-0.015	(-0.144)
Observations	489	125	364	489	
Panel B: Variables used in analysis (but not for matching)					
Operating cash (mil SEK)	-12.721	-14.910	-11.970	-2.940	(-0.812)
Sales (mil SEK)	16.634	15.655	16.970	-1.315	(-0.236)
VC funding (mil SEK)	13.442	23.079	10.132	12.947	(0.835)
Foreign subsidiary dummy	0.145	0.128	0.151	-0.023	(-0.652)
Observations	489	125	364	489	
Panel C: Other variables					
Assets (mil SEK)	31.607	33.900	30.820	3.080	(0.298)
ROA (%)	-67.106	-76.054	-64.033	-12.021	(-1.154)
Profitable	0.145	0.184	0.132	0.052	(1.334)
VC backed	0.403	0.424	0.396	0.028	(0.554)
Angel backed	0.047	0.064	0.041	0.023	(0.937)
Startup experience of managers	1.532	1.521	1.536	-0.016	(-0.068)
Same-industry startup exp of mgrs	0.433	0.500	0.410	0.090	(0.947)
VC experience of managers	0.038	0.045	0.035	0.010	(0.482)
USVC experience of managers	0.006	0.000	0.008	-0.008*	(-1.737)
Startup experience of directors	2.796	2.619	2.857	-0.238	(-0.963)
Same-industry startup exp of dirs	0.677	0.704	0.667	0.037	(0.424)
VC experience of directors	0.300	0.313	0.296	0.017	(0.308)
USVC experience of directors	0.060	0.070	0.056	0.014	(0.620)
Observations	489	125	364	489	

Table 2
Regression results around first US VC investment

This table presents regression results for the effects of receiving initial US VC funding underlying Figure 1. The dependent variables are cash from operations, sales, and VC funding. The unit of analysis is a company-year. Panel A shows results for regressions with a post dummy. For dependent variables in levels, we calculate effect sizes as the US VC × Post coefficient divided by the pre-period average of the dependent variable for the companies receiving US VC funding. For dependent variables in logs, we calculate effect sizes as $e^{USVC \times Post} - 1$. Panel B shows results for regressions with event time dummies. We report p-values from Wald tests for all pre-period US VC × Event time coefficients being jointly equal to zero, which formally tests for the existence of pre-trends between treated and control groups. For brevity, we omit the standalone US VC and Event time dummy coefficients. Table 1 describes the sample. Standard errors are clustered at the company-cohort level. *t*-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Post dummy			
	(1) Operating cash	(2) Sales (log)	(3) VC funding (log)
US VC × Post	-12.9191***	0.5127**	0.8288***
	(-3.734)	(2.431)	(5.425)
US VC	-1.1469	-0.4887**	-0.0035
	(-0.492)	(-2.343)	(-0.036)
Post	-6.8387***	0.9041***	0.2874***
	(-4.876)	(9.179)	(5.539)
Cohort FE	Yes	Yes	Yes
Observations	3,900	3,900	3,900
Adj. R^2	0.054	0.862	0.067
Effect size (%)	118	67	129
Panel B: Event time dummies			
US VC × Event time=-4	1.4271	0.0106	-0.0584
	(0.364)	(0.032)	(-0.276)
US VC × Event time=-3	5.5877*	-0.0053	-0.0377
	(1.692)	(-0.020)	(-0.171)
US VC × Event time=-2	2.5641	-0.2502	-0.1111
	(0.923)	(-1.052)	(-0.565)
US VC × Event time=0	-1.4144	-0.0194	1.0135***
	(-0.352)	(-0.093)	(5.126)
US VC × Event time=1	-4.9660	-0.0083	0.4841**
	(-1.098)	(-0.038)	(2.061)
US VC × Event time=2	-7.7771	0.3902	0.7761***
	(-1.417)	(1.505)	(2.744)
US VC × Event time=3	-14.8199**	0.7480***	0.6677**
	(-2.319)	(2.652)	(2.443)
US VC × Event time=4	-23.1082***	0.7042**	1.0052***
	(-2.727)	(2.139)	(3.260)
US VC × Event time=5	-26.1951***	0.8688**	1.0362***
	(-3.111)	(2.267)	(2.854)
US VC × Event time=6	-13.6655*	1.0899***	0.6503*
	(-1.830)	(2.774)	(1.739)
US VC × Event time=7	-10.1644	1.1519**	0.8421**
	(-0.868)	(2.192)	(1.978)
Cohort FE	Yes	Yes	Yes
Observations	3,900	3,900	3,900
Adj. R^2	0.062	0.866	0.167
Pre-trends Wald p-val	0.059	0.704	0.955

Table 3

VC investor characteristics

This table presents VC investors characteristics of companies receiving their first US VC investment and those receiving funding from non-US VC investors a year before the funding round. We require companies to have been in operation for at least one year prior to the funding round. VC firm AUM are in millions of real 2025 Swedish krona (SEK). Average Euro and US dollar to SEK exchange rates for December 2025 are 10.895 and 9.294, respectively. VC firm performance is the fraction of funded startups with an exit (IPO or acquisition). VC syndicate values in Panel A are the maximum value of VC firms within a syndicate.

	(1) Full	(2) US VC	(3) Non-US VC	(4) Difference	(5) t-statistic
Panel A: Company level: VC syndicate values					
VC firm AUM (mil SEK)	14117.647	40730.185	3407.723	37322.462**	(2.512)
VC firm funded startups	123.034	166.942	107.854	59.088***	(3.149)
VC firm performance	0.180	0.241	0.158	0.084***	(3.932)
Observations	489	125	364	489	
Panel B: Company-VC firm level: all observations					
VC firm AUM (mil SEK)	10699.702	21754.179	3035.735	18718.444***	(2.714)
VC firm funded startups	75.541	78.347	73.789	4.558	(0.486)
VC firm performance	0.139	0.153	0.130	0.024*	(1.924)
Observations	967	390	577	967	
Panel C: Company-VC firm level: within companies receiving initial US VC investment					
VC firm AUM (mil SEK)	21754.179	39912.810	7614.262	32298.548**	(2.079)
VC firm funded startups	78.347	118.642	51.933	66.709***	(4.181)
VC firm performance	0.153	0.160	0.149	0.010	(0.496)
Observations	390	160	230	390	

Table 4
Regression results in large and small VC subsamples

This table presents results for the regressions underlying Figure 2 and Figure 3. It shows the estimated effects of receiving initial US VC funding on cash from operations, sales, and VC funding in the large VC (models 1 to 3) and small VC (models 4 to 6) subsamples. We define large (small) VC as above (at or below) median VC syndicate AUM, where syndicate AUM is the maximum value of VC firm AUM within a syndicate. The unit of analysis is a company-year. Panel A shows results for regressions with a post dummy. For dependent variables in levels, we calculate effect sizes as the US VC × Post coefficient divided by the pre-period average of the dependent variable for the companies receiving US VC funding. For dependent variables in logs, we calculate effect sizes as $e^{USVC \times Post} - 1$. Panel B shows results for regressions with event time dummies. We report p-values from Wald tests for all pre-period US VC × Event time coefficients being jointly equal to zero, which formally tests for the existence of pre-trends between treated and control groups. For brevity, we omit the standalone US VC and Event time dummy coefficients. Standard errors are clustered at the company-cohort level. *t*-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Post dummy

	Large VC subsample			Small VC subsample		
	(1) Operating cash	(2) Sales (log)	(3) VC funding (log)	(4) Operating cash	(5) Sales (log)	(6) VC funding (log)
US VC × Post	12.3943	0.0074	0.7722**	-5.2258**	0.0907	0.5161***
	(0.897)	(0.017)	(2.079)	(-2.119)	(0.344)	(4.201)
US VC	6.5004	-0.6170	-0.5392	2.9344**	-0.6860**	-0.1502*
	(0.611)	(-1.331)	(-1.615)	(2.045)	(-2.430)	(-1.711)
Post	-42.3981***	1.8198***	0.6482**	-4.6791***	0.8816***	0.2813***
	(-3.378)	(5.165)	(2.356)	(-4.222)	(8.668)	(5.433)
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	678	678	678	3,222	3,222	3,222
Adj. R^2	0.157	0.899	0.100	0.044	0.866	0.050
Effect size (%)	-68	1	116	127	9	68

Panel B: Event time dummies

	(1) Operating cash	(2) Sales (log)	(3) VC funding (log)	(4) Operating cash	(5) Sales (log)	(6) VC funding (log)
US VC × Event time=-4	-28.6800**	-0.2562	0.4083	-1.8833	0.5144	0.2427
	(-2.020)	(-0.337)	(0.488)	(-0.760)	(1.065)	(0.851)
US VC × Event time=-3	-22.9342*	0.7577	0.6520	0.8743	0.1739	-0.0386
	(-1.931)	(1.136)	(0.885)	(0.493)	(0.474)	(-0.164)
US VC × Event time=-2	-9.5289	-0.2647	0.0134	-0.3664	-0.1295	-0.1066
	(-1.053)	(-0.518)	(0.018)	(-0.211)	(-0.399)	(-0.556)
US VC × Event time=0	-8.7142	-0.0954	0.8093	4.6802***	-0.2246	0.2937
	(-0.568)	(-0.260)	(1.454)	(2.635)	(-0.750)	(1.424)
US VC × Event time=1	15.8308	-0.4847	0.4516	-1.3495	-0.0824	0.4052*
	(0.817)	(-1.109)	(0.626)	(-0.438)	(-0.287)	(1.872)
US VC × Event time=2	8.9535	0.5121	1.0714	4.3798	-0.0274	0.4501*
	(0.448)	(1.025)	(1.169)	(1.231)	(-0.079)	(1.731)
US VC × Event time=3	-20.3663	0.6121	1.4556*	-5.6965	0.3083	0.5465**
	(-0.885)	(1.129)	(1.968)	(-1.406)	(0.821)	(1.991)
US VC × Event time=4	-23.9579	0.0832	1.5598	-13.7495**	0.0854	0.6654**
	(-0.829)	(0.135)	(1.638)	(-2.295)	(0.196)	(2.109)
US VC × Event time=5	-2.8016	-0.0663	1.5774*	-20.1191***	0.4748	0.8396**
	(-0.084)	(-0.093)	(1.723)	(-3.350)	(0.903)	(2.155)
US VC × Event time=6	13.4769	-0.4632	1.3391	-28.0398***	1.5124***	0.7625*
	(0.403)	(-0.612)	(1.344)	(-4.162)	(2.770)	(1.746)
US VC × Event time=7	-19.7703	-1.0539	2.1645***	-38.1177*	1.6768*	0.7972
	(-0.682)	(-1.210)	(2.846)	(-1.827)	(1.942)	(1.493)
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	678	678	678	3,222	3,222	3,222
Adj. R^2	0.176	0.908	0.222	0.058	0.869	0.157
Pre-trends Wald p-val	0.232	0.154	0.828	0.206	0.594	0.682

Table 5

New investors after first US VC investment

This table presents results for the regressions underlying Figure 4. It shows the estimated effects of receiving initial US VC funding on networks (cumulative number of new investors). We define large (small) VC as above (at or below) median VC syndicate AUM, where syndicate AUM is the maximum value of VC firm AUM within a syndicate. The unit of analysis is a company-year. We restrict observations to those in the post-period. Panel A shows results for regressions with a US VC dummy. We calculate effect sizes as the US VC coefficient divided by the post-period average of the dependent variable. Panel B shows results for regressions with US VC × Event time dummies, with event year zero omitted. For brevity, we omit the standalone US VC and Event time dummy coefficients. Standard errors are clustered at the company-cohort level. *t*-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: US VC dummy			
	Full sample	Large VC subsample	Small VC subsample
	(1) New investors	(2) New investors	(3) New investors
US VC	0.7801***	0.9731**	0.4556***
	(5.342)	(2.363)	(2.904)
Cohort FE	Yes	Yes	Yes
Observations	3,003	537	2,466
Adj. R^2	0.075	0.166	0.047
Effect size (%)	134	75	107
Panel B: Event time dummies			
US VC × Event time=1	0.3414***	0.3446	0.2111*
	(3.075)	(1.421)	(1.873)
US VC × Event time=2	0.5897***	0.6704**	0.3514**
	(4.070)	(2.115)	(2.374)
US VC × Event time=3	0.7691***	1.0207**	0.4368**
	(3.898)	(2.554)	(2.433)
US VC × Event time=4	1.1249***	1.0465	0.5855***
	(4.343)	(1.626)	(2.602)
US VC × Event time=5	1.2979***	0.4760	0.9281***
	(4.370)	(0.610)	(3.006)
US VC × Event time=6	1.2737***	0.0804	1.0038***
	(3.963)	(0.095)	(2.592)
US VC × Event time=7	1.4365***	-0.1722	1.1063**
	(3.574)	(-0.182)	(2.501)
Cohort FE	Yes	Yes	Yes
Observations	3,003	537	2,466
Adj. R^2	0.161	0.281	0.122

Table 6
New investors from inside and outside of networks after first US VC

This table presents results for the regressions underlying Figure 5. It shows the estimated effects of receiving initial US VC funding on the cumulative number of new large investors as well as new investors from inside and outside of the networks of $t = 0$ investors. The unit of analysis is a company-year. We restrict observations to those in the post-period. Panel A shows results for regressions with a US VC dummy. We calculate effect sizes as the US VC coefficient divided by the post-period average of the dependent variable. Panel B shows results for regressions with US VC × Event time dummies, with event year zero omitted. For brevity, we omit the standalone US VC and Event time dummy coefficients. Standard errors are clustered at the company-cohort level. *t*-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: US VC dummy

	Small VC subsample	Full sample	
	(1) New large investors	(2) New within-networks investors	(3) New outside-networks investors
US VC	0.1133*	0.1467***	0.6335***
	(1.727)	(3.095)	(5.227)
Cohort FE	Yes	Yes	Yes
Observations	2,466	3,009	3,009
Adj. R^2	0.049	0.049	0.070
Effect size (%)	184	131	135

Panel B: Event time dummies

	(1)	(2)	(3)
US VC × Event time=1	0.0097	0.1056**	0.2363***
	(0.305)	(2.356)	(2.622)
US VC × Event time=2	0.0503	0.1325***	0.4583***
	(1.009)	(2.684)	(3.752)
US VC × Event time=3	0.0695	0.1404**	0.6303***
	(1.135)	(2.431)	(3.695)
US VC × Event time=4	0.1142	0.2151***	0.9118***
	(1.044)	(2.961)	(4.046)
US VC × Event time=5	0.3096*	0.2494***	1.0508***
	(1.726)	(2.849)	(4.233)
US VC × Event time=6	0.3848	0.2126**	1.0624***
	(1.366)	(2.249)	(4.048)
US VC × Event time=7	0.2386	0.2638**	1.1740***
	(1.158)	(2.320)	(3.475)
Cohort FE	Yes	Yes	Yes
Observations	2,466	3,009	3,009
Adj. R^2	0.068	0.077	0.150

Table 7
First US-syndicator VC investment as treatment

This table presents regression results for the effects of receiving initial US-syndicator VC funding (US-synd VC) in the never-US VC subsample underlying Figure 6. We define initial US-syndicator as an investment by a non-US VC firm that has previously co-invested with a US VC. The dependent variables are cash from operations, sales, and VC funding. The unit of analysis is a company-year. Panel A shows results for regressions with a post dummy. For dependent variables in levels, we calculate effect sizes as the US-synd VC × Post coefficient divided by the pre-period average of the dependent variable for the companies receiving US-synd funding. For dependent variables in logs, we calculate effect sizes as $e^{US-synd \times Post} - 1$. Panel B shows results for regressions with event time dummies. We report p-values from Wald tests for all pre-period US-synd VC × Event time coefficients being jointly equal to zero, which formally tests for the existence of pre-trends between treated and control groups. For brevity, we omit the standalone US-synd VC and Event time dummy coefficients. Table IA.1 describes the sample. Standard errors are clustered at the company-cohort level. *t*-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Post dummy			
	(1) Operating cash	(2) Sales (log)	(3) VC funding (log)
US-synd VC × Post	0.2675	-0.1029	0.1305***
	(0.257)	(-0.787)	(2.645)
US-synd VC	-0.1813	-0.2974**	-0.0235
	(-0.277)	(-2.291)	(-0.928)
Post	-6.0409***	0.8029***	0.4821***
	(-7.215)	(8.525)	(13.589)
Cohort FE	Yes	Yes	Yes
Observations	8,258	8,258	8,258
Adj. R^2	0.033	0.860	0.064
Effect size (%)	-12	-10	14
Panel B: Event time dummies			
US-synd VC × Event time=-4	-1.1902	-0.0376	0.0679
	(-1.214)	(-0.194)	(1.284)
US-synd VC × Event time=-3	-1.1507	-0.0696	-0.0104
	(-1.636)	(-0.402)	(-0.232)
US-synd VC × Event time=-2	-0.4529	0.0655	-0.0853*
	(-0.632)	(0.456)	(-1.759)
US-synd VC × Event time=0	-0.4787	-0.0139	0.3696***
	(-0.562)	(-0.118)	(3.779)
US-synd VC × Event time=1	0.2011	-0.1456	0.1920***
	(0.192)	(-1.143)	(2.725)
US-synd VC × Event time=2	1.3549	-0.0275	0.0197
	(0.992)	(-0.184)	(0.211)
US-synd VC × Event time=3	-1.5164	-0.0483	0.0693
	(-1.044)	(-0.302)	(0.796)
US-synd VC × Event time=4	-0.1409	-0.2612	-0.0207
	(-0.076)	(-1.388)	(-0.228)
US-synd VC × Event time=5	-0.4042	-0.1300	-0.0028
	(-0.186)	(-0.622)	(-0.027)
US-synd VC × Event time=6	-0.4684	-0.1272	0.0623
	(-0.190)	(-0.522)	(0.671)
US-synd VC × Event time=7	-2.1752	-0.2407	0.0293
	(-0.780)	(-0.831)	(0.264)
Cohort FE	Yes	Yes	Yes
Observations	8,258	8,258	8,258
Adj. R^2	0.034	0.862	0.182
Pre-trends Wald p-val	0.415	0.851	0.040

Table 8
First US-LP VC investment as treatment

This table presents regression results for the effects of receiving initial US-LP VC funding in the never-US VC subsample underlying Figure 7. The dependent variables are cash from operations, sales, and VC funding. The unit of analysis is a company-year. Panel A shows results for regressions with a post dummy. For dependent variables in levels, we calculate effect sizes as the US-LP VC × Post coefficient divided by the pre-period average of the dependent variable for the companies receiving US-LP VC funding. For dependent variables in logs, we calculate effect sizes as $e^{US-LP\times Post} - 1$. Panel B shows results for regressions with event time dummies. We report p-values from Wald tests for all pre-period US-LP VC × Event time coefficients being jointly equal to zero, which formally tests for the existence of pre-trends between treated and control groups. For brevity, we omit the standalone US-LP VC and Event time dummy coefficients. Table IA.4 describes the sample. Standard errors are clustered at the company-cohort level. *t*-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Post dummy

	(1) Operating cash	(2) Sales (log)	(3) VC funding (log)
US-LP VC × Post	-7.5168**	0.2627	0.4703***
	(-2.083)	(0.973)	(3.709)
US-LP VC	0.7067	-0.2882	-0.0364
	(0.410)	(-1.349)	(-0.730)
Post	-4.2994***	0.8447***	0.5876***
	(-3.849)	(6.204)	(10.736)
Cohort FE	Yes	Yes	Yes
Observations	2,191	2,191	2,191
Adj. R^2	0.073	0.890	0.090
Effect size (%)	183	30	60

Panel B: Event time dummies

	(1) Operating cash	(2) Sales (log)	(3) VC funding (log)
US-LP VC × Event time=-4	2.0493	0.2563	0.0435
	(1.043)	(0.710)	(0.477)
US-LP VC × Event time=-3	1.9102	0.0433	0.0385
	(1.055)	(0.123)	(0.286)
US-LP VC × Event time=-2	1.8320	-0.0593	-0.2035*
	(1.381)	(-0.216)	(-1.935)
US-LP VC × Event time=0	-0.8963	0.1264	0.8348***
	(-0.574)	(0.538)	(4.044)
US-LP VC × Event time=1	-3.5866	0.1547	0.2949
	(-1.382)	(0.567)	(1.411)
US-LP VC × Event time=2	-2.5740	0.2260	0.0501
	(-0.730)	(0.718)	(0.225)
US-LP VC × Event time=3	-7.3724	0.2624	0.2428
	(-1.446)	(0.760)	(1.067)
US-LP VC × Event time=4	-19.2451**	0.5212	0.8061**
	(-2.416)	(1.089)	(2.314)
US-LP VC × Event time=5	-15.4957	0.7201	0.4669
	(-1.415)	(1.207)	(1.149)
US-LP VC × Event time=6	-5.0380	1.0607	-0.0557
	(-0.493)	(1.559)	(-0.484)
US-LP VC × Event time=7	-19.7707	1.5448*	-0.0179
	(-1.393)	(1.814)	(-0.137)
Cohort FE	Yes	Yes	Yes
Observations	2,191	2,191	2,191
Adj. R^2	0.079	0.893	0.230
Pre-trends Wald p-val	0.581	0.845	0.037

Table 9

First US-LP VC investment as treatment with matching on investor size

This table presents regression results for the effects of receiving initial US-LP VC funding in the never-US VC subsample with matching on investor size underlying Figure 8. The dependent variables are cash from operations, sales, and VC funding. We include a dummy equal to one if a startup is backed by a large investor, which we define as a non-US VC firm with AUM above the median AUM of US VC firms, as an additional matching variable. The unit of analysis is a company-year. Panel A shows results for regressions with a post dummy. For dependent variables in levels, we calculate effect sizes as the US-LP VC × Post coefficient divided by the pre-period average of the dependent variable for the companies receiving US-LP VC funding. For dependent variables in logs, we calculate effect sizes as $e^{US-LP \times Post} - 1$. Panel B shows results for regressions with event time dummies. We report p-values from Wald tests for all pre-period US-LP VC × Event time coefficients being jointly equal to zero, which formally tests for the existence of pre-trends between treated and control groups. For brevity, we omit the standalone US-LP VC and Event time dummy coefficients. Table IA.5 describes the sample. Standard errors are clustered at the company-cohort level. *t*-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Post dummy

	(1) Operating cash	(2) Sales (log)	(3) VC funding (log)
US-LP VC × Post	-4.0487	0.0085	0.3684***
	(-1.348)	(0.029)	(2.719)
US-LP VC	-1.4234	-0.1146	0.0143
	(-1.437)	(-0.512)	(0.238)
Post	-4.1128***	0.9862***	0.5550***
	(-5.785)	(6.767)	(9.548)
Cohort FE	Yes	Yes	Yes
Observations	1,714	1,714	1,714
Adj. R^2	0.109	0.904	0.082
Effect size (%)	114	1	45

Panel B: Event time dummies

	(1) Operating cash	(2) Sales (log)	(3) VC funding (log)
US-LP VC × Event time=-4	1.2273	0.4181	0.0024
	(0.839)	(1.032)	(0.023)
US-LP VC × Event time=-3	0.7041	0.0125	-0.0153
	(0.483)	(0.032)	(-0.088)
US-LP VC × Event time=-2	0.0813	-0.2966	-0.3044**
	(0.067)	(-0.971)	(-2.448)
US-LP VC × Event time=0	-1.1212	0.0264	0.5968***
	(-0.647)	(0.102)	(2.760)
US-LP VC × Event time=1	-3.3612	-0.1069	0.2019
	(-1.375)	(-0.343)	(0.863)
US-LP VC × Event time=2	1.2301	-0.1850	-0.1429
	(0.434)	(-0.515)	(-0.626)
US-LP VC × Event time=3	-1.8612	-0.0644	0.1156
	(-0.503)	(-0.168)	(0.482)
US-LP VC × Event time=4	-7.7002	0.2201	0.9543**
	(-1.457)	(0.467)	(2.394)
US-LP VC × Event time=5	-16.8769**	0.1966	0.3642
	(-2.128)	(0.289)	(0.775)
US-LP VC × Event time=6	-4.0370	0.3598	-0.1705
	(-0.510)	(0.491)	(-1.282)
US-LP VC × Event time=7	-15.9448	1.0125	-0.0439
	(-1.161)	(1.070)	(-0.340)
Cohort FE	Yes	Yes	Yes
Observations	1,714	1,714	1,714
Adj. R^2	0.120	0.908	0.218
Pre-trends Wald p-val	0.816	0.291	0.026

Internet Appendix for

Financing J-Curves in Venture Capital

Thomas Hellmann, Alexander Montag, Joacim Tåg

A Financial statements

This section outlines the income statement and balance sheet items from the annual reports submitted to the Swedish Companies Registration Office and shows how we use these to construct cash flow statements.

We are interested in studying how companies use cash flows. The annual reports submitted to the Companies Registration Office include an income statement and a balance sheet, neither of which directly shows how cash is spent or generated. The balance sheet shows the aggregate net change in cash from the previous to the current fiscal year. The income statement lists income and expense items that reflect economic activity regardless of when cash is exchanged.[13] It recognizes economic activity by matching revenue and expenses when a transaction occurs, and not when a payment is made.[14] We therefore use the income statement and balance sheet information to construct cash flow statements. Section A.1 uses a stylized example to illustrate how the income statement and balance sheet record transactions, and how the timing of these can be different from when cash is exchanged.

To give some intuition for how we construct the cash flow statements, we use the property of the balance sheet that the total of the left-hand side (assets) is equal to the total of the right-hand side (liabilities and equity).

$$Assets = Liabilities + Equity \tag{2}$$

This implies that the changes from one fiscal year to the next must also be equal on both sides of the balance sheet.

$$\Delta Assets = \Delta Liabilities + \Delta Equity \tag{3}$$

We can decompose the change in assets into the change in cash and the change in all other items, and then solve for the change in cash.

$$\Delta Cash = -\Delta \textit{Non-cash assets} + \Delta Liabilities + \Delta Equity \tag{4}$$

The cash flow statement breaks down the net change in cash on the balance sheet into cash provided by or used for operating, investing, and financing activities during a fiscal year. To compute the net cash from operating activities, we take the net profit/loss from the income statement and adjust it by using non-cash items from the income statement as well as changes in current asset and current liability accounts from the balance sheet. For example, we add back depreciation expenses which decrease net profit but do not involve a cash outflow. Most adjustments to compute the net cash from financing activities involve summing up changes in non-current liability and equity accounts. We calculate the net cash from investing activities as a balancing amount by taking the net change in cash on the balance sheet and subtracting the sum of net cash from operating and financing activities. Figure IA.11 illustrates how we use items from the income statement and balance sheet account categories to construct the cash flow

[13]This is known as accrual accounting.

[14]This is known as matching principle.

statement activities.[15] Section A.4 outlines all adjustments we make to construct cash flow statements.

A limitation of the data is that we can only observe net changes in balance sheet items and not all underlying transactions. Ideally, we would break down net changes in balance sheet items into transactions that involve cash and those that do not. We would then only use transactions that involve cash and assign each to either operating, investing, or financing activities. For example, the net change in the balance sheet item machinery can combine the purchase of a new machine for cash (involves cash) and depreciation (does not involve cash). The purchase decreases *Cash* and increases *Non-cash assets* in Equation 4 by the same amount. Depreciation, on the other hand, decreases both *Non-cash assets* and *Equity* on the right-hand side of Equation 4, leaving cash unchanged. Using the net change in machinery when constructing the cash flow statement would understate the cash outflow from investing activities.

Using net changes in balance sheet items introduces the largest measurement error in the calculation of net cash from investing activities because non-cash transactions account for a relatively large part of non-current assets. Net cash from operating and financing activities should be mostly unaffected. The biggest source of measurement error in net cash from operating activities is most likely the difference between observable tax expenses on the income statement and unobservable actual taxes paid (the effective tax rate). We do not expect this to have a significant effect because our sample consists of young companies for whom tax optimization is probably not that important. Using net changes in balance sheet items for constructing the cash flow statement should not affect the calculation of net cash from financing activities.

We compute net cash from investing activities by taking the net change in cash on the balance sheet and subtracting the sum of net cash from operating and financing activities. This minimizes the measurement error in breaking down the net change in cash into net cash from each of the three activity categories (operating, investing, financing) by trading off granularity in investing activities. We calculate net cash from investing activities as a balancing amount as opposed to the sum of cash from different investing activities.

Companies can choose between the nature of expense and cost of sales accounting types when preparing the income statement. The nature of expense method is easier to follow because it assigns expenses to categories (e.g., raw materials or depreciation), whereas the cost of sales method breaks down expenses according to their function (e.g., cost of goods sold or administrative expenses). The main drawback of the nature of expense method is that the income statement does not show a gross profit. Almost all income statements in our dataset follow the nature of expense method, and companies rarely switch accounting types. Sections A.2.1 and A.2.2 outline income statement items for the nature of expense and cost of sales accounting types, respectively. Similarly, Sections A.4.1 and A.4.2 show how we construct cash flow statements for either accounting type.

Smaller companies have the option to submit abridged annual reports. We find that these companies often leave the most granular balance sheet items blank and only provide the total for that account category. For example, total inventories is much less likely to be missing than its two components work

[15] Opening balances of balance sheet accounts for first fiscal years are zero.

in progress and other inventories. We therefore use the total amounts of account categories instead of the respective component accounts to construct cash flow statements for smaller companies. Abridged annual reports: Cash flow statement outlines all adjustments that we make when constructing cash flow statements for smaller companies.

A.1 Stylized example

This section uses a stylized example to illustrate how transactions are recorded on the balance sheet and income statement, and that the timing of these can be different from when cash is exchanged.

A company produces a good in period 1, sells the good on account in period 2, and receives payment for the sold good in period 3. In period 1, the asset side of the balance sheet shows a decrease in raw materials and a complementary increase in finished goods reflecting the production costs of the good. This is known as an asset swap because total assets remain unchanged. The income statement does not record anything. In period 2, the asset side of the balance sheet shows a decrease in finished goods by the production costs and an increase in accounts receivable by the sales price. This usually results in an increase of total assets because the sales price of a good is typically higher than its production costs. The income statement reports the sales price of the good as revenue and its production costs as expense. The sales profit appears as net income on the income statement and increases retained earnings (part of equity) on the balance sheet. Both sides of the balance sheet increase by the same amount, the sales profit. In period 3, the balance sheet shows another asset swap with an increase in cash and a decrease in accounts receivable by the sales price. Again, the income statement does not record anything.

This stylized example shows that the company records a profit on the income statement and balance sheet at the time of the sale (period 2), and not when it receives the cash payment (period 3). We therefore create cash flow statements, which reflect when cash is exchanged, to study how companies manage cash flows.

A.2 Income statement

A.2.1 Nature of expense method

Item

Net sales
$\pm$ Inventory change
$\pm$ Capitalized work
$+$ Other operating income
$-$ Raw materials and consumables
$-$ Goods for resale
$-$ Other external expenses
$-$ Salaries and benefits

− Depreciation
± Financial items affecting comparability
− Other operating expenses

Operating profit/loss

± Profit/loss from group companies
+ Interest income from group companies
+ External interest income
+ Other financial income
− Interest expenses to group companies
− External interest expenses
− Other financial expenses

Profit/loss after net financial income

+ Extraordinary income
− Extraordinary expenses
± Group contributions
± Shareholders' contributions
± Appropriations
− Taxes
± Minority shareholdings

Net profit/loss

A.2.2 Cost of sales method

Item

Net sales
− Cost of goods sold

Gross profit/loss

− Selling expenses
− Administrative expenses
− R&D expenses
± Financial items affecting comparability
+ Other operating income
− Other operating expenses

Operating profit/loss

± Profit/loss from group companies
+ Interest income from group companies
+ External interest income

+ Other financial income
− Interest expenses to group companies
− External interest expenses
− Other financial expenses

Profit/loss after net financial income

+ Extraordinary income
− Extraordinary expenses
± Group contributions
± Shareholders' contributions
± Appropriations
− Taxes
± Minority shareholdings

Net profit/loss

A.3 Balance sheet

Item

Assets
Cash
Short-term investments

Accounts receivable
Current receivables from group/associated companies
Other current receivables
Total current receivables

Work in progress
Other inventories
Total inventories

Total current assets

Participation in group/associated companies
Long-term receivables from group/associated companies
Loans to partners and related parties
Other financial assets
Total financial assets

Buildings and land
Machinery
Equipment
Machinery and equipment

Other tangible fixed assets
Total tangible fixed assets

Subscribed capital unpaid
Capitalized R&D expenses
Patents, licenses, concessions etc.
Goodwill
Other intangible fixed assets
Total intangible fixed assets

Total fixed assets

Total assets

Liabilities and equity
Current liabilities to credit institutions
Accounts payable
Current liabilities to group/associated companies
Other current liabilities

Total current liabilities

Untaxed reserves
Minority shareholding
Provisions
Bonds

Non-current liabilities to credit institutions
Non-current liabilities to group/associated companies
Other non-current liabilities

Total non-current liabilities

Nominal share capital
Share premium reserve
Revaluation reserve
Other restricted equity

Profit/loss brought forward
Group contributions
Shareholders' contributions
Profit/loss for the year

Total equity

Total liabilities and equity

A.4 Cash flow statement

A.4.1 Nature of expense method

Item

OPERATING ACTIVITIES

Net profit/loss

+ Depreciation

− Group contributions

− Shareholders' contributions

− Appropriations

− Δ Accounts receivable

− Δ Current receivables from group/associated companies

− Δ Other current receivables

− Δ Work in progress

− Δ Other inventories

+ Δ Current liabilities to credit institutions

+ Δ Accounts payable

+ Δ Current liabilities to group/associated companies

+ Δ Other current liabilities

+ Δ Deferred taxes

Net cash provided by/used in operating activities

FINANCING ACTIVITIES

Group contributions

+ Shareholders' contributions

+ Appropriations

− Dividends

+ Δ Bonds

+ Δ Non-current liabilities to credit institutions

+ Δ Non-current liabilities to group/associated companies

+ Δ Other non-current liabilities

+ Δ Nominal share capital

+ Δ Share premium reserve

+ Δ Revaluation reserve

+ Δ Other restricted equity

Net cash provided by/used in financing activities

INVESTING ACTIVITIES

Δ Cash
− Net cash provided by/used in operating activities
− Net cash provided by/used in financing activities

Net cash provided by/used in investing activities

A.4.2 Cost of sales method

Item

OPERATING ACTIVITIES

Net profit/loss
+ Depreciation of cost of goods sold
+ Depreciation of selling expenses
+ Depreciation of administrative expenses
+ Depreciation of R&D expenses
+ Depreciation of other operating expenses
+ Unspecified depreciations
− Group contributions
− Shareholders' contributions
− Appropriations
− Δ Accounts receivable
− Δ Current receivables from group/associated companies
− Δ Other current receivables
− Δ Work in progress
− Δ Other inventories
+ Δ Current liabilities to credit institutions
+ Δ Accounts payable
+ Δ Current liabilities to group/associated companies
+ Δ Other current liabilities
+ Δ Deferred taxes

Net cash provided by/used in operating activities

FINANCING ACTIVITIES

Group contributions
+ Shareholders' contributions
+ Appropriations
− Dividends
+ Δ Bonds
+ Δ Non-current liabilities to credit institutions

+ Δ Non-current liabilities to group/associated companies
+ Δ Other non-current liabilities
+ Δ Nominal share capital
+ Δ Share premium reserve
+ Δ Revaluation reserve
+ Δ Other restricted equity

Net cash provided by/used in financing activities

INVESTING ACTIVITIES

Δ Cash
− Net cash provided by/used in operating activities
− Net cash provided by/used in financing activities

Net cash provided by/used in investing activities

A.5 Abridged annual reports: Cash flow statement

This section shows how we construct cash flow statements for companies that submit abridged annual reports to the Swedish Companies Registration Office.

A.5.1 Nature of expense method

Item

OPERATING ACTIVITIES

Net profit/loss
+ Depreciation
− Group contributions
− Shareholders' contributions
− Appropriations
− Δ Total current receivables
− Δ Total inventories
+ Δ Total current liabilities
+ Δ Deferred taxes

Net cash provided by/used in operating activities

FINANCING ACTIVITIES

Group contributions
+ Shareholders' contributions
+ Appropriations

− Dividends
+ Δ Bonds
+ Δ Total non-current liabilities
+ Δ Nominal share capital
+ Δ Share premium reserve
+ Δ Revaluation reserve
+ Δ Other restricted equity

Net cash provided by/used in financing activities

INVESTING ACTIVITIES

Δ Cash
− Net cash provided by/used in operating activities
− Net cash provided by/used in financing activities

Net cash provided by/used in investing activities

A.5.2 Cost of sales method

Item

OPERATING ACTIVITIES

Net profit/loss
+ Depreciation of cost of goods sold
+ Depreciation of selling expenses
+ Depreciation of administrative expenses
+ Depreciation of R&D expenses
+ Depreciation of other operating expenses
+ Unspecified depreciations
− Group contributions
− Shareholders' contributions
− Appropriations
− Δ Total current receivables
− Δ Total inventories
+ Δ Total current liabilities
+ Δ Deferred taxes

Net cash provided by/used in operating activities

FINANCING ACTIVITIES

Group contributions
+ Shareholders' contributions

$+$ Appropriations

$-$ Dividends

$+ \Delta$ Bonds

$+ \Delta$ Total non-current liabilities

$+ \Delta$ Nominal share capital

$+ \Delta$ Share premium reserve

$+ \Delta$ Revaluation reserve

$+ \Delta$ Other restricted equity

Net cash provided by/used in financing activities

INVESTING ACTIVITIES

Δ Cash

$-$ Net cash provided by/used in operating activities

$-$ Net cash provided by/used in financing activities

Net cash provided by/used in investing activities

B Sample

This section describes the sample construction process in detail. We begin with an overview of the data sources. We then describe and motivate the steps in creating the analysis sample.

B.1 Data sources

We use administrative data from the Swedish Companies Registration Office covering the population of limited liability companies between 1998 and 2023. The limited liability company is the dominant organizational form for Swedish startups and is the only form that provides limited liability to all shareholders. The data include complete balance sheets, income statements, and supplementary disclosures.

We do the following steps to refine these administrative company data. First, when both consolidated and unconsolidated accounts are available, we use consolidated statements, as they better capture a company's overall economic activity. We next adjust financial statements data for inflation by converting all nominal values into December 2025 real values. This ensures comparability of values across time and is particularly important given that our data span 25 years. We then generate annualized flow variables (e.g., sales) to account for the fact that some fiscal years are shorter or longer than 12 months. Last, we use income statement and balance sheet items to construct cash flow statements. Section A describes this in detail.

We obtain venture capital investments and exits data from PitchBook, Crunchbase, and VentureXpert. We use three separate sources of VC data to increase coverage. These datasets include detailed information on startups (e.g., industry, location), funding rounds (e.g., amount, date), exit events (e.g., type, date), and investors (e.g., assets under management, year founded). Because our analysis focuses on investor origin, we manually collect the headquarters location of VC firms when this information is missing. Further, we augment information on limited partners, which is only available in PitchBook, by manually collecting additional data from Preqin and CapitalIQ.

We combine these separate datasets to create a "master" VC dataset in the following way. First, we match startups by company name and location to create a "master" startup dataset that maps startups across the PitchBook, Crunchbase, and VentureXpert datasets. This dataset lists each unique startup, alongside a newly created "master" company ID, as well as the corresponding company IDs in PitchBook, Crunchbase, and VentureXpert. 60% of startups appear in one VC dataset, 29% in two, and 11% in all three. This highlights the advantage of combining these three datasets for increasing coverage. Second, we repeat the matching process for VC firms to create a "master" VC firm dataset. We then combine funding rounds appearing in multiple databases by collapsing events occurring within 34 days of each other. This cutoff ensures that the distribution of days between funding rounds in our "master" VC dataset is similar to the distributions in the individual VC databases. When combining funding rounds, we keep mode values of numerical variables (e.g., round amount) and all the associated investors. We keep the first observed exit for each startup. As a last step, and as with the financial statements data, we convert VC investment and exit values to real 2025 Swedish krona (SEK) to account for inflation.

B.2 Sample construction

We construct our sample in two steps. We first create a company-year panel of startups that ever raise VC funding. We then use this to create a cohort-based matched-controls sample, which we use in a stacked difference-in-differences design.

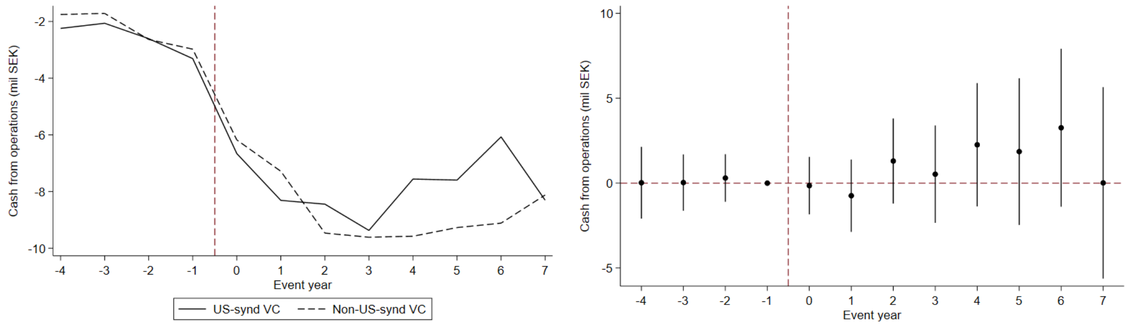
We construct the company-year panel of startups that ever raise VC funding by matching companies in the administrative data from the Swedish Companies Registration Office and those in the "master" VC dataset by company name and city. For companies with a single exact name match, we retain that match. For companies with multiple name matches, we retain the observation with a unique city match.

We create the cohort-based matched-controls sample in the following way. We first construct event-specific datasets for each year in which US VC investments occur. Each dataset includes startups receiving their first US VC investment in that year and a matched set of companies receiving non-US VC investments in the same year. We match initial-US VC and non-US VC startups jointly on the following four characteristics measured a year before the focal funding round: industry (3 bins), investment stage (3 bins), EBITDA (quartiles), and number of employees (quartiles). We require companies to have been in operation for at least one year prior to investment. We further exclude startups that previously received US VC funding but do not receive such funding in the focal year, ensuring that the benchmark group has no US VC exposure at event time zero. Importantly, we do not impose any such restriction on the post-period. We focus on event-specific datasets between 2000 and 2020 to ensure that startups have at least three possible post-period observations. As a last step, we keep four pre- and eight post-period observations for each company.

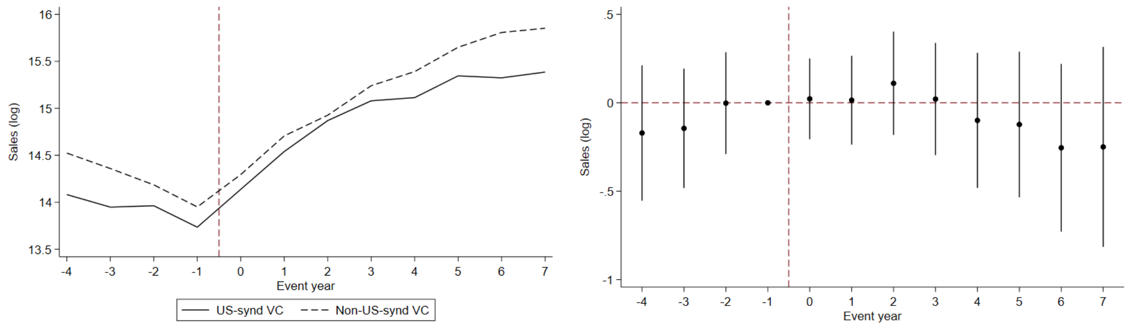
Our matching approach ensures that we compare startups receiving their first US VC funding to those receiving non-US VC funding that operate in a similar industry, raise funding at a similar stage, and have similar operating earnings as well as company size. With US VC investments occurring between 2000 and 2020, we construct 21 event-specific cohorts, which we then stack and align using normalized event time relative to the year of the first US VC investment.

In summary, we start the sample construction process with the population of 1,097,365 Swedish limited liability companies between 1998 and 2023. We then restrict these to the subset of 4,510 companies that ever raise VC funding, out of which 292 raise US VC funding. Imposing the requirement that we observe one year of pre-investment data reduces the sample to 3,924 observations. As a final step, we create a cohort-based matched-controls sample of 489 companies raising VC funding between 2000 and 2020, of which 125 raise US VC financing.

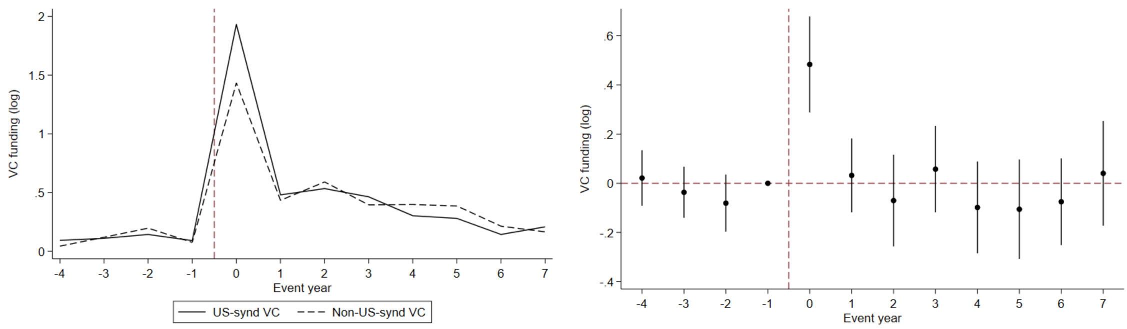
How do observable company characteristics evolve across successive sample restrictions? Starting from all VC rounds (4,510 observations), startups at the time of the first round exhibit average sales of SEK 28 million, operating losses of SEK 13 million, and 18 employees. Restricting to startups with at least one year of pre-investment data (3,924 observations) yields nearly identical profiles, with only modest increases in sales (SEK 32 million) and employment (20 employees), and no meaningful change in operating losses or the prevalence of angel backing. Finally, in the matched cohort sample (489 observations), companies remain comparable along these dimensions, with slightly lower sales (SEK 25 million) and somewhat larger operating losses (SEK 19 million), but similar size and financing patterns.



A: Cash from operations

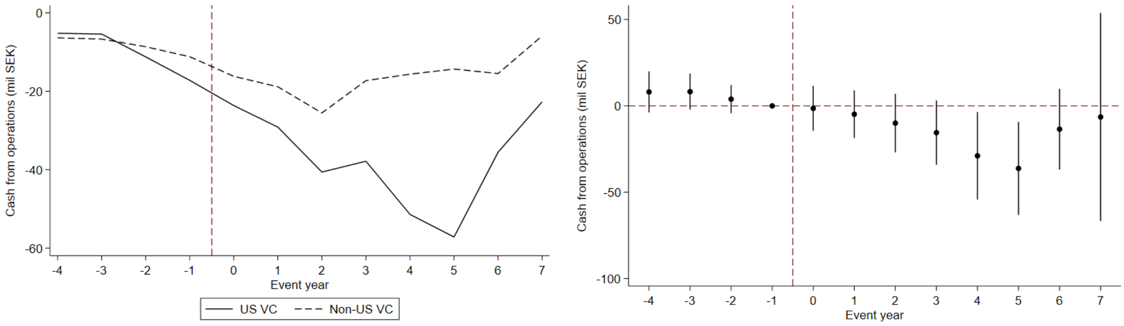


B: Sales

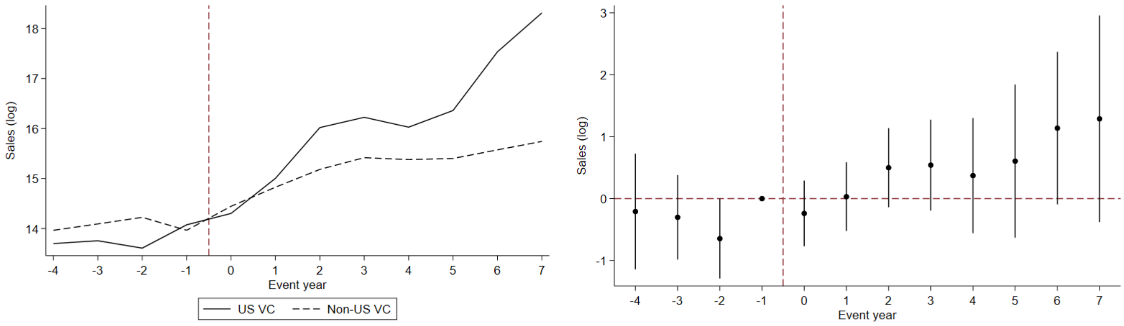


C: VC funding

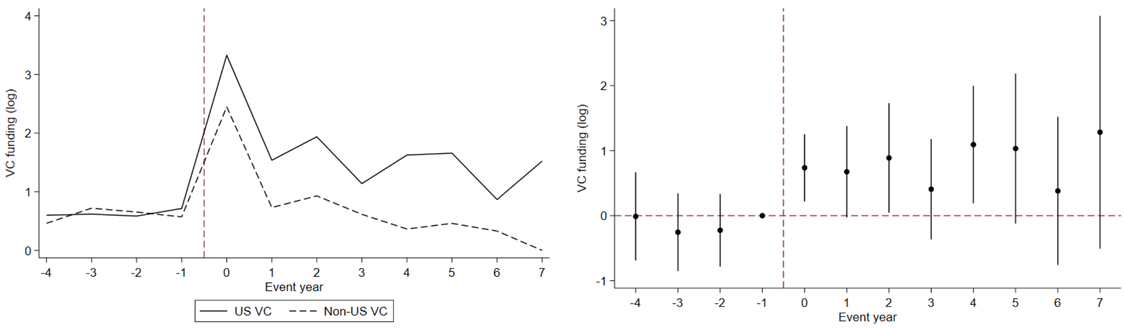
Figure IA.1. Outcomes around first US-syndicator VC investment in never-US VC subsample, with alternative US-syndicator definition. This figure shows the effects of receiving initial US-syndicator VC funding on cash from operations, sales, and VC funding in the never-US VC subsample. We define initial US-syndicator as an investment by a non-US VC firm that has previously co-invested with a US VC in a startup that has exited successfully. It displays the raw means for companies receiving their first US-synd VC investment and those receiving funding from non-US-synd VC investors (left) as well as DiD coefficients estimated by event time with 95% confidence intervals (right). Table IA.2 describes the sample and Table IA.3 shows the regression results underlying these event time figures.



A: Cash from operations

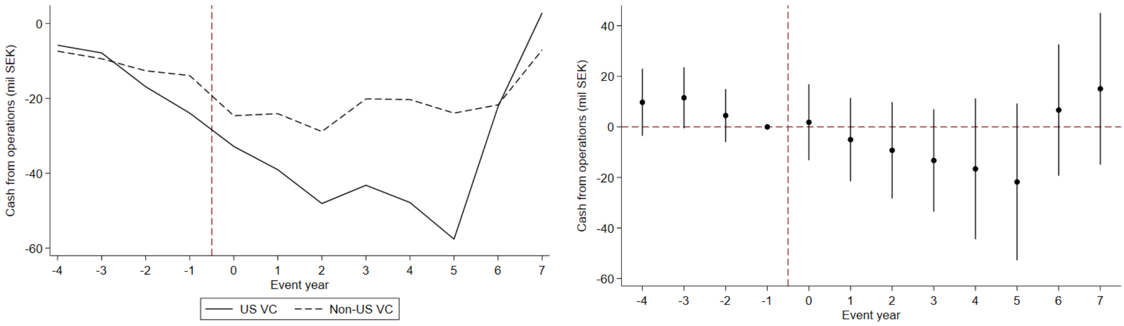


B: Sales

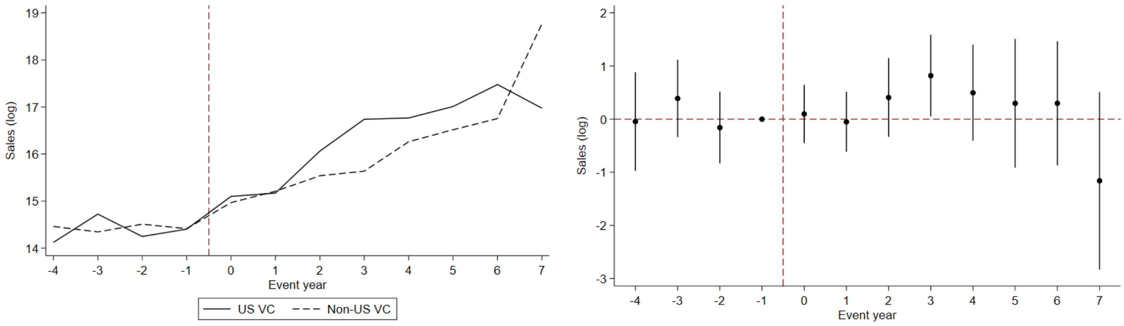


C: VC funding

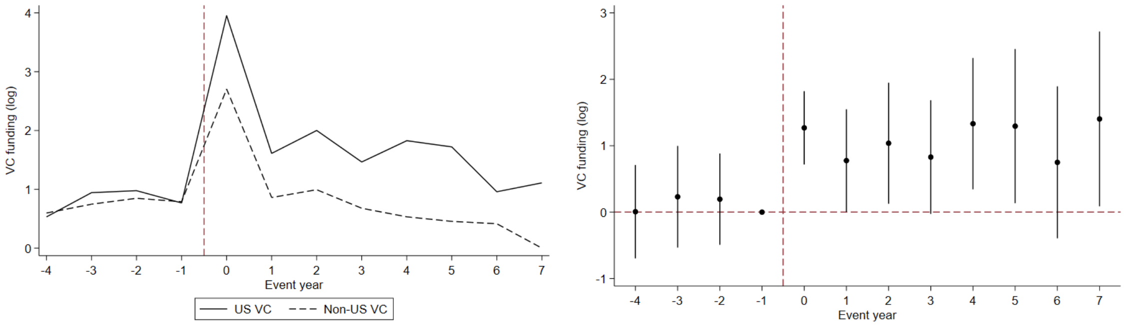
Figure IA.2. Outcomes around first US VC investment in experienced VC firm subsample. This figure shows the effects of receiving initial US VC funding on cash from operations, sales, and VC funding. It displays the raw means for companies receiving their first US VC investment and those receiving funding from non-US VC investors (left) as well as DiD coefficients estimated by event time with 95% confidence intervals (right). We define experienced VC as above median VC syndicate funded startups, where syndicate funded startups is the maximum value of VC firm funded startups within a syndicate. Table IA.6 shows the regression results underlying these event time figures.



A: Cash from operations

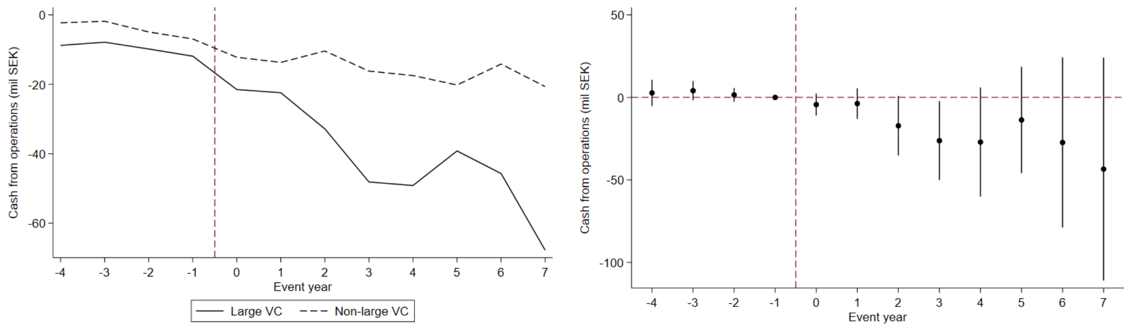


B: Sales

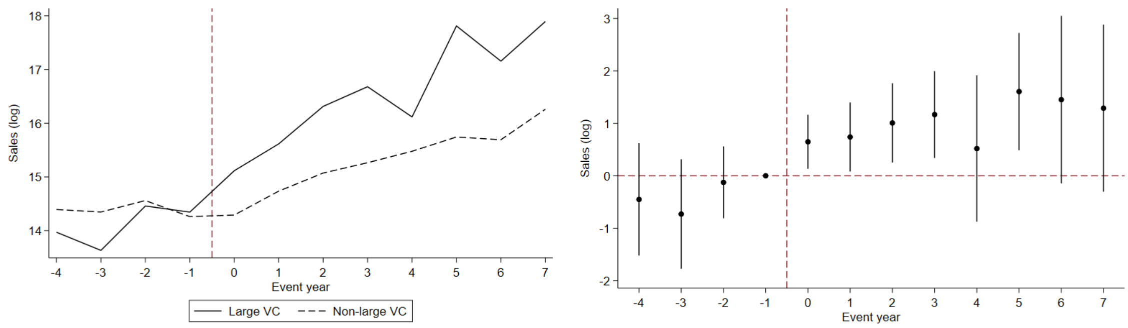


C: VC funding

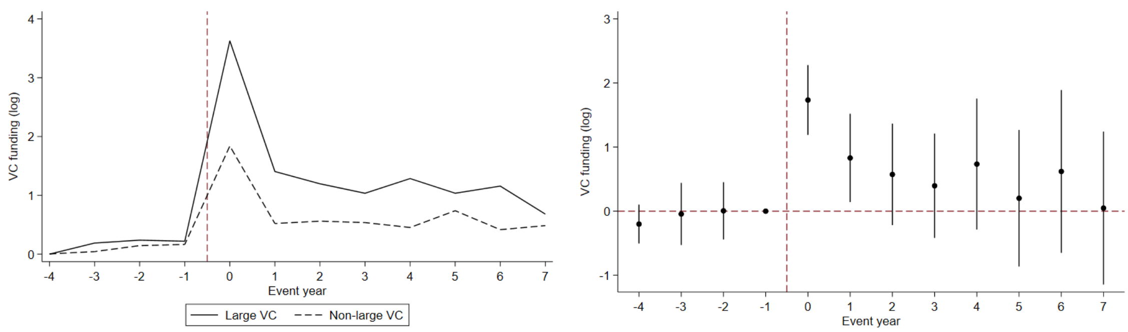
Figure IA.3. Outcomes around first US VC investment in successful VC firm subsample. This figure shows the effects of receiving initial US VC funding on cash from operations, sales, and VC funding. It displays the raw means for companies receiving their first US VC investment and those receiving funding from non-US VC investors (left) as well as DiD coefficients estimated by event time with 95% confidence intervals (right). We define successful VC as above median VC syndicate performance, where syndicate performance is the maximum value of VC firm performance (fraction of funded startups with an exit) within a syndicate. Table IA.6 shows the regression results underlying these event time figures.



A: Cash from operations



B: Sales



C: VC funding

Figure IA.4. Outcomes around first large VC investment in never-US VC subsample. This figure shows the effects of receiving initial large VC funding on cash from operations, sales, and VC funding in the never-US VC subsample. We define initial large VC as an investment by a non-US VC firm that has above median US VC firm AUM. It displays the raw means for companies receiving their first large VC investment and those receiving funding from non-large VC investors (left) as well as DiD coefficients estimated by event time with 95% confidence intervals (right). Table IA.7 describes the sample and Table IA.8 shows the regression results underlying these event time figures.

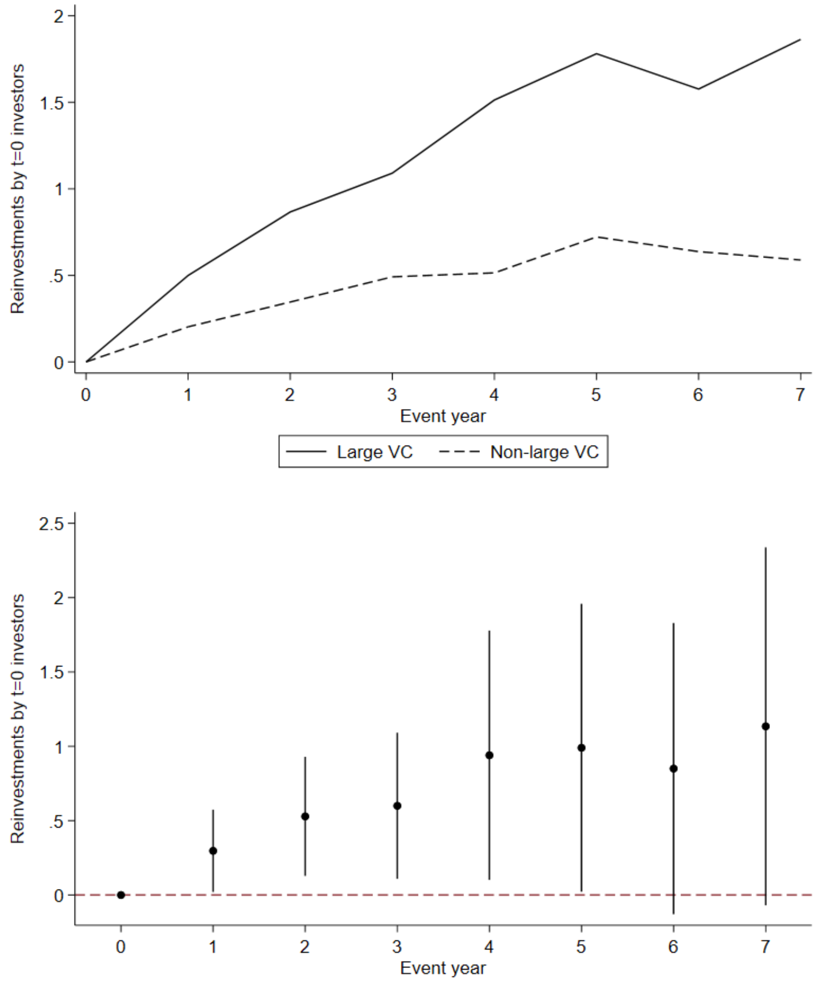
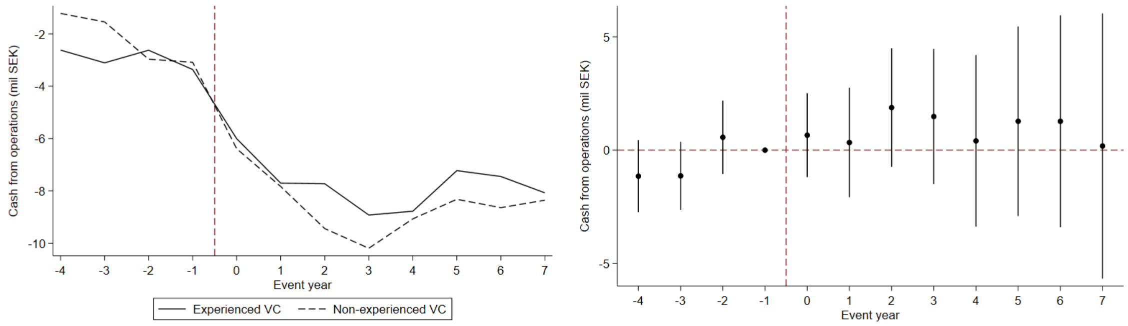
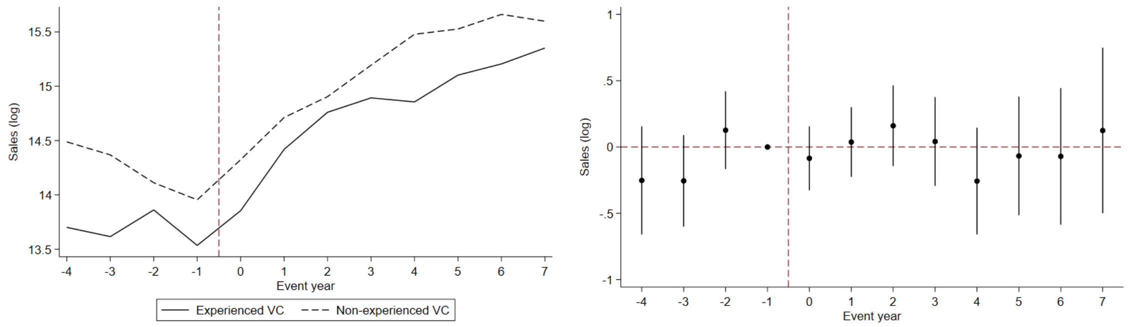


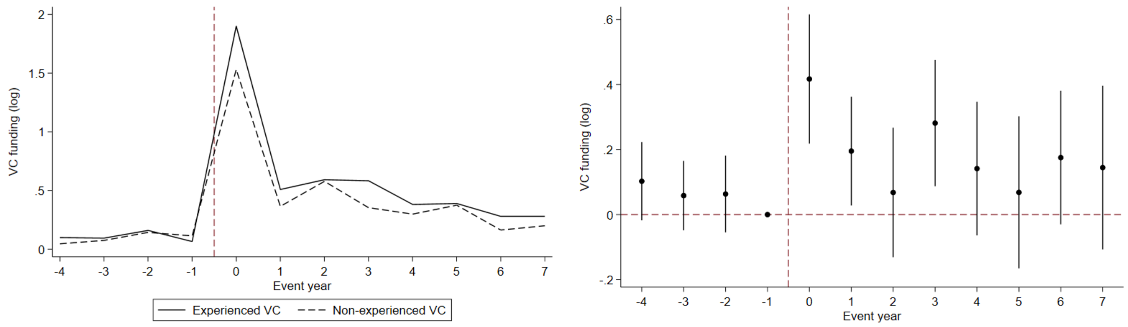
Figure IA.5. Reinvestments following first large VC investment in never-US VC subsample. This figure shows the effects of receiving initial large VC funding on reinvestments by $t = 0$ investors in the never-US VC subsample. We define initial large VC as an investment by a non-US VC firm that has above median US VC firm AUM. It displays the raw means for companies receiving their first large VC investment and those receiving funding from non-large VC investors (left) as well as event time regression coefficients from a regression run only in the post period with event year zero omitted and with 95% confidence intervals (right). Table IA.7 describes the sample and Table IA.9 shows the regression results underlying these event time figures.



A: Cash from operations

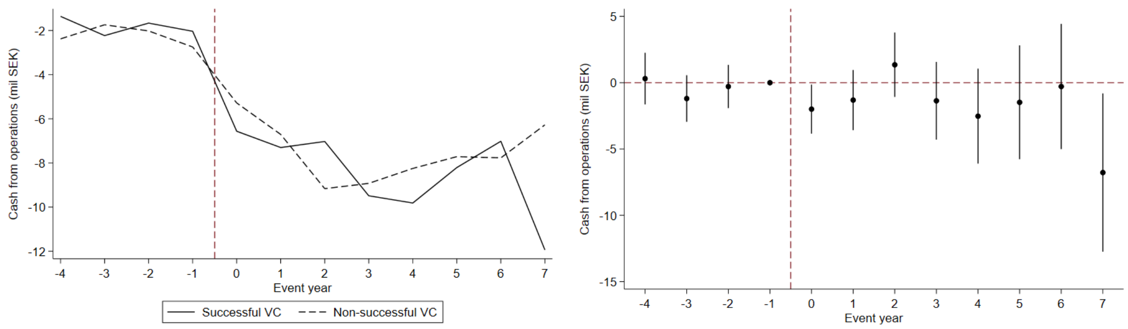


B: Sales

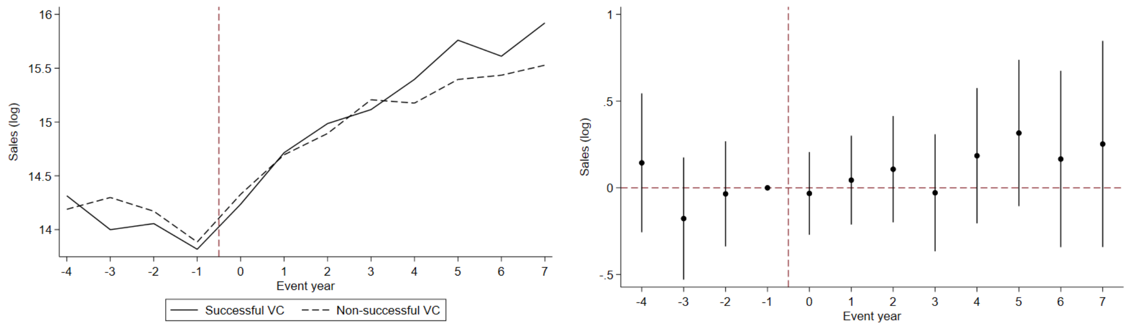


C: VC funding

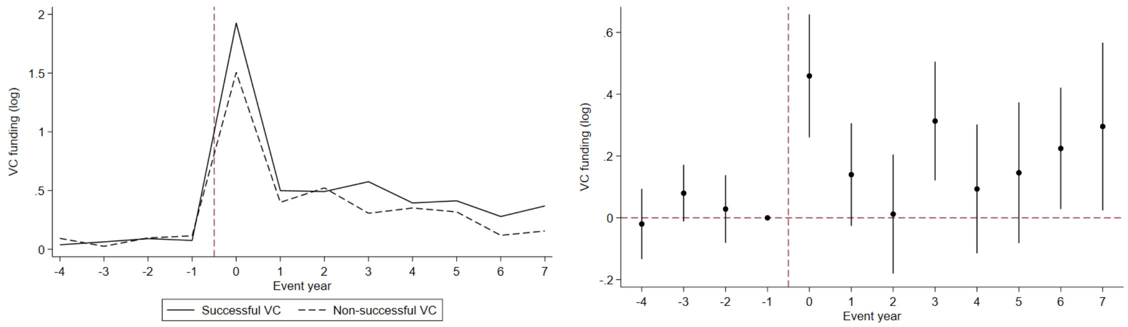
Figure IA.6. Outcomes around first experienced VC investment in never-US VC subsample. This figure shows the effects of receiving initial experienced VC funding on cash from operations, sales, and VC funding in the never-US VC subsample. We define initial experienced VC as an investment by a non-US VC firm that has above median US VC firm funded startups. It displays the raw means for companies receiving their first experienced VC investment and those receiving funding from non-experienced VC investors (left) as well as DiD coefficients estimated by event time with 95% confidence intervals (right). Table IA.10 describes the sample and Table IA.11 shows the regression results underlying these event time figures.



A: Cash from operations

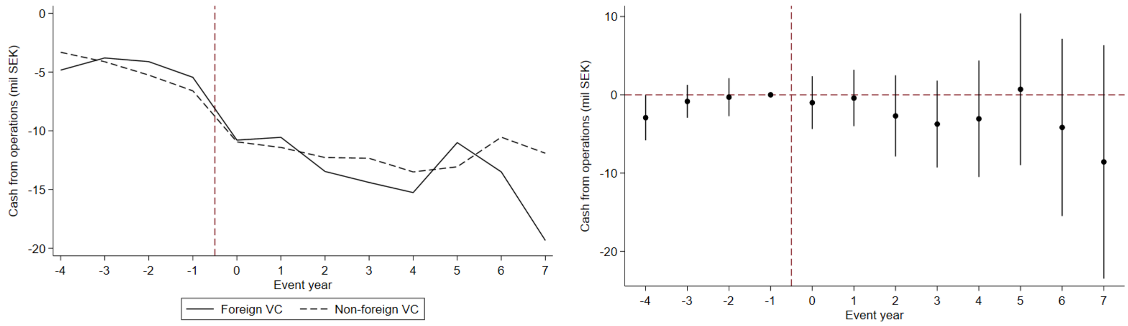


B: Sales

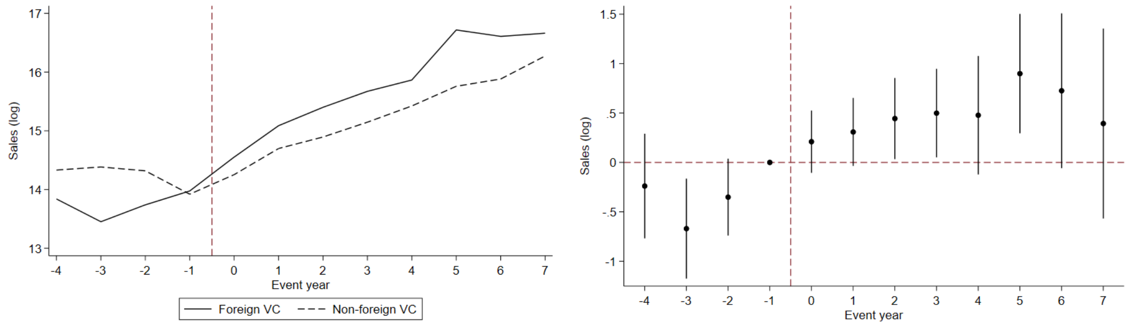


C: VC funding

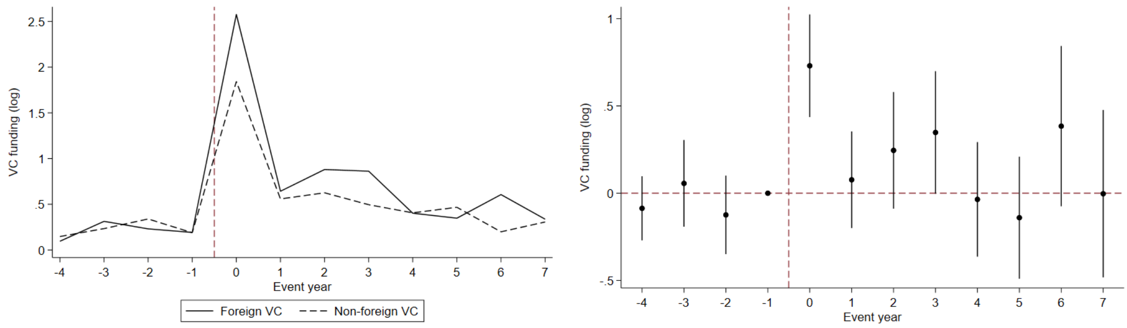
Figure IA.7. Outcomes around first successful VC investment in never-US VC subsample. This figure shows the effects of receiving initial successful VC funding on cash from operations, sales, and VC funding in the never-US VC subsample. We define initial successful VC as an investment by a non-US VC firm that has above median US VC firm performance, where performance is measured as the fraction of funded startups with an exit. It displays the raw means for companies receiving their first successful VC investment and those receiving funding from non-successful VC investors (left) as well as DiD coefficients estimated by event time with 95% confidence intervals (right). Table IA.12 describes the sample and Table IA.13 shows the regression results underlying these event time figures.



A: Cash from operations

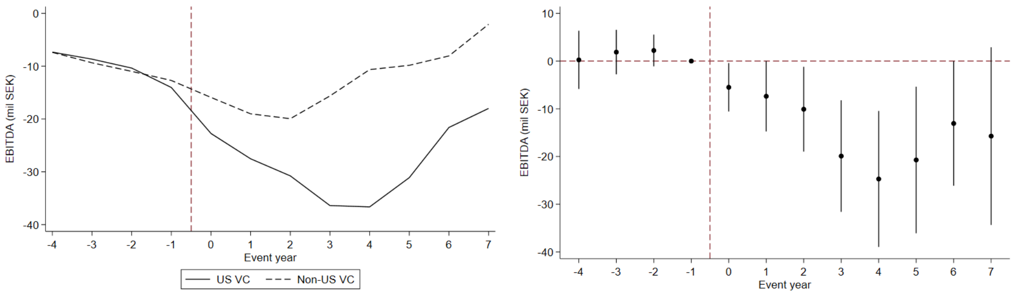


B: Sales

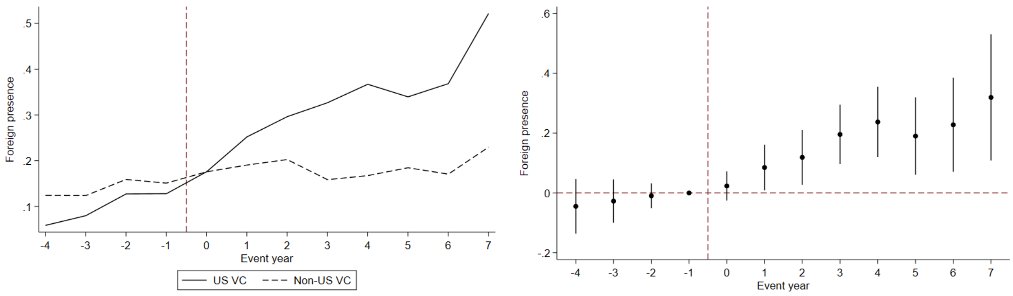


C: VC funding

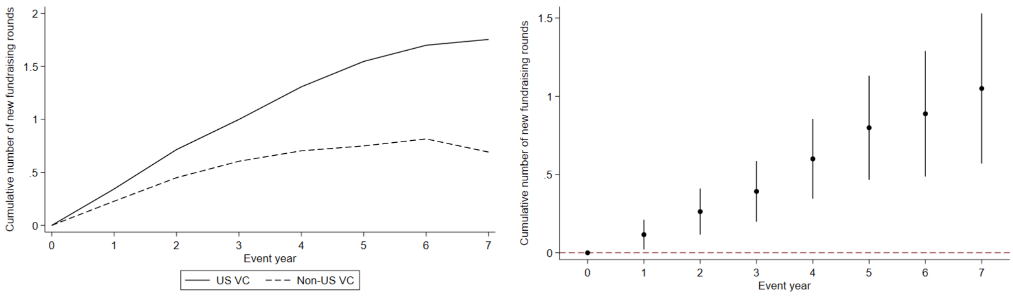
Figure IA.8. Outcomes around first foreign VC investment in never-US VC subsample. This figure shows the effects of receiving initial foreign VC funding on cash from operations, sales, and VC funding in the never-US VC subsample. It displays the raw means for companies receiving their first foreign VC investment and those receiving funding from non-foreign VC investors (left) as well as DiD coefficients estimated by event time with 95% confidence intervals (right). Table IA.14 describes the sample and Table IA.15 shows the regression results underlying these event time figures.



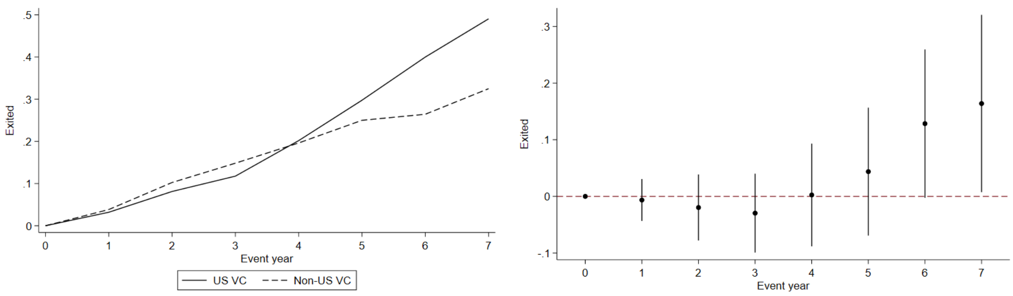
A: EBITDA



B: Foreign presence



C: Follow-on funding rounds



D: Exits

Figure IA.9. Alternative measures of outcome variables. This figure shows the effects of receiving initial US VC funding on alternative measures of outcome variables. It displays the raw means for companies receiving their first US VC investment and those receiving funding from non-US VC investors (left) as well as event time regression coefficients from a regression with event year minus one (A and B) or zero omitted (C and D) and with 95% confidence intervals (right). Table IA.18 shows the regression results underlying these event time figures.

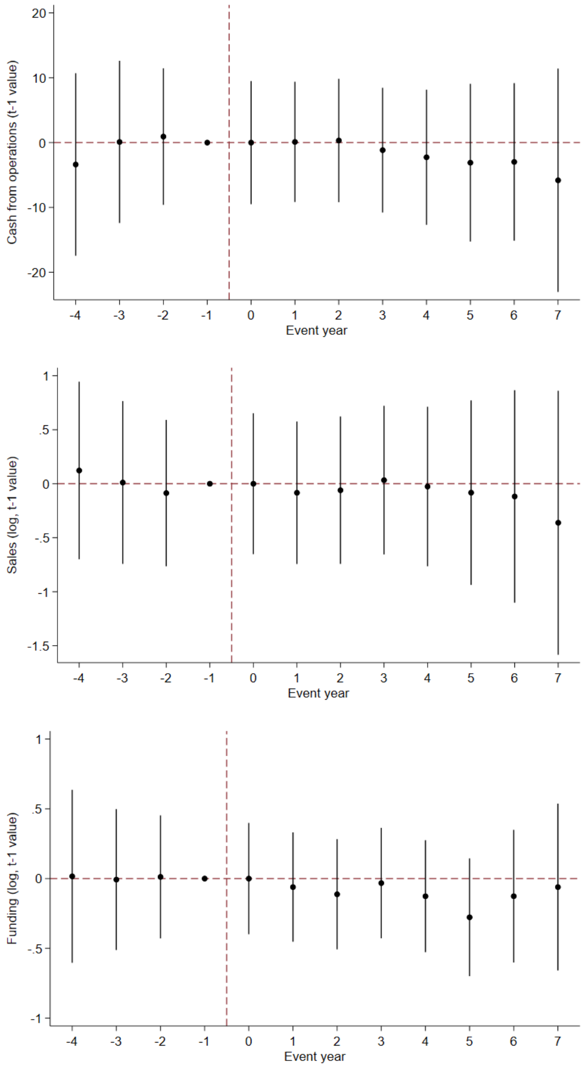


Figure IA.10. Attrition. The figures reports coefficients from a dynamic stacked difference-in-differences model with values of cash from operations, sales, and funding measured at $t-1$ as dependent variable. The figures indicate that there is no statistically significant selection effects out of the sample on the basis of pre-investment cash from operations, sales, or funding.

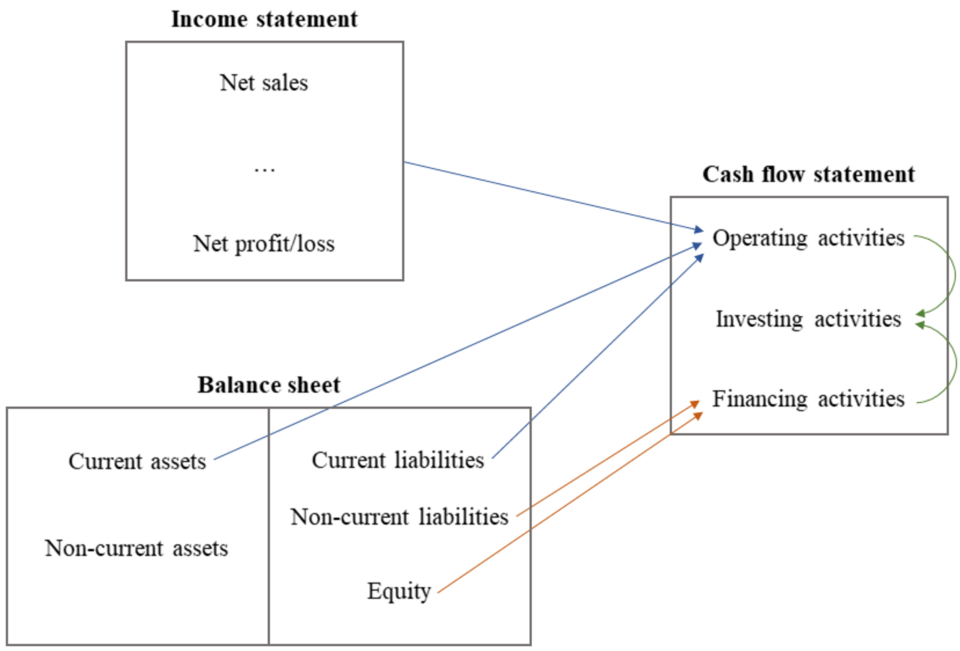


Figure IA.11. Financial statements. This figure illustrates how we use items from the income statement and balance sheet account categories to construct the cash flow statement activities.

Table IA.1
Descriptive statistics: First US-syndicator VC investment as treatment

This table presents descriptive statistics by comparing companies receiving their first US-syndicator VC investment (US-synd VC) and those receiving funding from non-US-syndicator VC investors in the never-US VC subsample a year before the funding round. We define initial US-syndicator as an investment by a non-US VC firm that has previously co-invested with a US VC. We require companies to have been in operation for at least one year prior to the funding round. EBITDA, operating cash, sales, VC round amount, and assets are in millions of real 2025 Swedish krona (SEK). Average Euro and US dollar to SEK exchange rates for December 2025 are 10.895 and 9.294, respectively. When constructing our matched sample, we match jointly on industry (3 bins), stage (3 bins), EBITDA at $t-1$ (quartiles), and number of employees at $t-1$ (quartiles). Section 3 describes the sample construction process in more detail. Panel A shows continuous versions of the variables used for the matching, except for industry. A χ^2-test for differences in the distribution of companies receiving initial US-synd VC and non-US-synd VC funding across industries (using all levels) at $t-1$ is insignificant with a p-value of 0.473. Panel B shows variables used in the analysis but not for the matching, and Panel C shows other variables.

	(1) Full	(2) US-synd VC	(3) Non-US-synd VC	(4) Difference	(5) t-statistic
Panel A: Variables used for matching					
EBITDA (mil SEK)	-3.283	-3.260	-3.308	0.048	(0.061)
Employees	7.385	6.444	8.426	-1.982*	(-1.667)
Round number	0.122	0.116	0.129	-0.012	(-0.454)
Observations	998	524	474	998	
Panel B: Variables used in analysis (but not for matching)					
Operating cash (mil SEK)	-2.757	-2.561	-2.973	0.413	(0.539)
Sales (mil SEK)	12.408	9.694	15.407	-5.713*	(-1.720)
Round amount (mil USD)	0.482	0.558	0.398	0.159	(0.524)
Foreign subsidiary dummy	0.065	0.063	0.068	-0.005	(-0.289)
Observations	998	524	474	998	
Panel C: Other variables					
Assets (mil SEK)	14.280	11.528	17.322	-5.794*	(-1.842)
ROA (%)	-42.794	-41.548	-44.172	2.625	(0.545)
Profitable	0.222	0.227	0.217	0.010	(0.372)
VC backed	0.097	0.090	0.105	-0.016	(-0.837)
Angel backed	0.038	0.031	0.046	-0.016	(-1.296)
Startup experience of managers	1.198	1.112	1.294	-0.183	(-1.350)
Same-industry startup exp of mgrs	0.355	0.337	0.374	-0.037	(-0.655)
VC experience of managers	0.050	0.069	0.028	0.041	(1.599)
USVC experience of managers	0.009	0.010	0.009	0.001	(0.099)
Startup experience of directors	2.650	2.627	2.676	-0.050	(-0.278)
Same-industry startup exp of dirs	0.677	0.682	0.670	0.012	(0.194)
VC experience of directors	0.189	0.227	0.146	0.081***	(2.603)
USVC experience of directors	0.026	0.026	0.026	0.000	(0.000)
Observations	998	524	474	998	

Table IA.2
Descriptive statistics: Alternative definition of first US-syndicator VC

This table presents descriptive statistics by comparing companies receiving their first US-syndicator VC investment (US-synd VC) and those receiving funding from non-US-syndicator VC investors in the never-US VC subsample a year before the funding round. We define initial US-syndicator as an investment by a non-US VC firm that has previously co-invested with a US VC in a startup that has exited successfully. We require companies to have been in operation for at least one year prior to the funding round. EBITDA, operating cash, sales, VC round amount, and assets are in millions of real 2025 Swedish krona (SEK). Average Euro and US dollar to SEK exchange rates for December 2025 are 10.895 and 9.294, respectively. When constructing our matched sample, we match jointly on industry (3 bins), stage (3 bins), EBITDA at $t-1$ (quartiles), and number of employees at $t-1$ (quartiles). Section 3 describes the sample construction process in more detail. Panel A shows continuous versions of the variables used for the matching, except for industry. A χ^2-test for differences in the distribution of companies receiving initial US-synd VC and non-US-synd VC funding across industries (using all levels) at $t-1$ is insignificant with a p-value of 0.605. Panel B shows variables used in the analysis but not for the matching, and Panel C shows other variables.

	(1) Full	(2) US-synd VC	(3) Non-US-synd VC	(4) Difference	(5) t-statistic
Panel A: Variables used for matching					
EBITDA (mil SEK)	-3.646	-4.031	-3.314	-0.717	(-0.847)
Employees	7.784	7.213	8.279	-1.066	(-0.854)
Round number	0.156	0.148	0.163	-0.016	(-0.516)
Observations	1,006	467	539	1,006	
Panel B: Variables used in analysis (but not for matching)					
Operating cash (mil SEK)	-3.130	-3.309	-2.975	-0.334	(-0.399)
Sales (mil SEK)	13.275	10.688	15.517	-4.829	(-1.377)
Round amount (mil USD)	1.295	1.241	1.341	-0.100	(-0.113)
Foreign subsidiary dummy	0.068	0.073	0.063	0.010	(0.609)
Observations	1,006	467	539	1,006	
Panel C: Other variables					
Assets (mil SEK)	15.911	13.527	17.977	-4.450	(-1.252)
ROA (%)	-43.546	-42.930	-44.080	1.150	(0.241)
Profitable	0.216	0.221	0.212	0.009	(0.347)
VC backed	0.115	0.109	0.121	-0.011	(-0.565)
Angel backed	0.039	0.032	0.045	-0.012	(-1.028)
Startup experience of managers	1.239	1.141	1.326	-0.185	(-1.332)
Same-industry startup exp of mgrs	0.361	0.339	0.381	-0.042	(-0.744)
VC experience of managers	0.065	0.078	0.053	0.025	(0.716)
USVC experience of managers	0.014	0.013	0.014	-0.001	(-0.108)
Startup experience of directors	2.673	2.691	2.656	0.035	(0.198)
Same-industry startup exp of dirs	0.666	0.687	0.648	0.039	(0.641)
VC experience of directors	0.196	0.234	0.162	0.072**	(2.172)
USVC experience of directors	0.027	0.028	0.026	0.002	(0.207)
Observations	1,006	467	539	1,006	

Table IA.3
Alternative definition of first US-syndicator VC as treatment

This table presents regressions results for the effects of receiving initial US-syndicator VC funding (US-synd VC) in the never-US VC subsample underlying Figure IA.1. We define initial US-syndicator as an investment by a non-US VC firm that has previously co-invested with a US VC in a startup that has exited successfully. The dependent variables are cash from operations, sales, and VC funding. The unit of analysis is a company-year. Panel A shows results for regressions with a post dummy. For dependent variables in levels, we calculate effect sizes as the US-synd VC × Post coefficient divided by the pre-period average of the dependent variable for the companies receiving US-synd VC funding. For dependent variables in logs, we calculate effect sizes as $e^{US-synd \times Post} - 1$. Panel B shows results for regressions with event time dummies. We report p-values from Wald tests for all pre-period US-synd VC × Event time coefficients being jointly equal to zero, which formally tests for the existence of pre-trends between treated and control groups. For brevity, we omit the standalone US-synd VC and Event time dummy coefficients. Table IA.2 describes the sample. Standard errors are clustered at the company-cohort level. *t*-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Post dummy			
	(1) Operating cash	(2) Sales (log)	(3) VC funding (log)
US-synd VC × Post	0.7121	0.0283	0.0895*
	(0.718)	(0.218)	(1.787)
US-synd VC	-0.2947	-0.2327*	0.0003
	(-0.419)	(-1.807)	(0.010)
Post	-6.1654***	0.7362***	0.5035***
	(-7.628)	(8.414)	(14.106)
Cohort FE	Yes	Yes	Yes
Observations	8,296	8,296	8,296
Adj. R^2	0.033	0.861	0.065
Effect size (%)	-26	3	9

Panel B: Event time dummies			
US-synd VC × Event time=-4	0.0219	-0.1707	0.0213
	(0.020)	(-0.875)	(0.370)
US-synd VC × Event time=-3	0.0340	-0.1444	-0.0368
	(0.040)	(-0.840)	(-0.695)
US-synd VC × Event time=-2	0.3006	-0.0019	-0.0808
	(0.422)	(-0.013)	(-1.367)
US-synd VC × Event time=0	-0.1490	0.0223	0.4834***
	(-0.173)	(0.192)	(4.855)
US-synd VC × Event time=1	-0.7408	0.0146	0.0320
	(-0.682)	(0.114)	(0.418)
US-synd VC × Event time=2	1.3027	0.1102	-0.0704
	(1.020)	(0.739)	(-0.741)
US-synd VC × Event time=3	0.5256	0.0211	0.0574
	(0.359)	(0.131)	(0.642)
US-synd VC × Event time=4	2.2578	-0.0995	-0.0984
	(1.220)	(-0.511)	(-1.035)
US-synd VC × Event time=5	1.8575	-0.1226	-0.1057
	(0.844)	(-0.584)	(-1.025)
US-synd VC × Event time=6	3.2621	-0.2543	-0.0752
	(1.376)	(-1.052)	(-0.836)
US-synd VC × Event time=7	0.0144	-0.2494	0.0403
	(0.005)	(-0.865)	(0.371)
Cohort FE	Yes	Yes	Yes
Observations	8,296	8,296	8,296
Adj. R^2	0.034	0.864	0.179
Pre-trends Wald p-val	0.971	0.730	0.399

Table IA.4
Descriptive statistics: First US-LP VC investment as treatment

This table presents descriptive statistics by comparing companies receiving their first US-LP VC investment and those receiving funding from non-US-LP VC investors in the never-US VC subsample a year before the funding round. We require companies to have been in operation for at least one year prior to the funding round. EBITDA, operating cash, sales, VC round amount, and assets are in millions of real 2025 Swedish krona (SEK). Average Euro and US dollar to SEK exchange rates for December 2025 are 10.895 and 9.294, respectively. When constructing our matched sample, we match jointly on industry (3 bins), stage (3 bins), EBITDA at $t-1$ (quartiles), and number of employees at $t-1$ (quartiles). Section 3 describes the sample construction process in more detail. Panel A shows continuous versions of the variables used for the matching, except for industry. A χ^2-test for differences in the distribution of companies receiving initial US-LP VC and non-US-LP VC funding across industries (using all levels) at $t-1$ is insignificant with a p-value of 0.485. Panel B shows variables used in the analysis but not for the matching, and Panel C shows other variables.

	(1) Full	(2) US-LP VC	(3) Non-US-LP VC	(4) Difference	(5) t-statistic
Panel A: Variables used for matching					
EBITDA (mil SEK)	-5.260	-5.661	-5.098	-0.563	(-0.324)
Employees	7.418	6.343	7.854	-1.511	(-0.788)
Round number	0.142	0.181	0.127	0.054	(0.775)
Observations	288	83	205	288	
Panel B: Variables used in analysis (but not for matching)					
Operating cash (mil SEK)	-4.946	-5.713	-4.636	-1.077	(-0.621)
Sales (mil SEK)	8.288	4.241	9.927	-5.686*	(-1.722)
Round amount (mil USD)	2.229	0.720	2.839	-2.119	(-0.842)
Foreign subsidiary dummy	0.080	0.096	0.073	0.023	(0.622)
Observations	288	83	205	288	
Panel C: Other variables					
Assets (mil SEK)	13.265	9.187	14.917	-5.730	(-1.302)
ROA (%)	-53.076	-63.462	-48.870	-14.592	(-1.246)
Profitable	0.188	0.120	0.215	-0.094**	(-2.046)
VC backed	0.108	0.133	0.098	0.035	(0.817)
Angel backed	0.045	0.060	0.039	0.021	(0.718)
Startup experience of managers	1.609	1.494	1.655	-0.161	(-0.450)
Same-industry startup exp of mgrs	0.561	0.556	0.564	-0.008	(-0.055)
VC experience of managers	0.099	0.148	0.079	0.069	(0.879)
USVC experience of managers	0.035	0.049	0.030	0.020	(0.477)
Startup experience of directors	2.698	3.322	2.447	0.875*	(1.802)
Same-industry startup exp of dirs	0.770	0.810	0.754	0.055	(0.458)
VC experience of directors	0.275	0.296	0.267	0.029	(0.325)
USVC experience of directors	0.037	0.040	0.036	0.005	(0.231)
Observations	288	83	205	288	

Table IA.5

Descriptive statistics: First US-LP VC as treatment with matching on investor size

This table presents descriptive statistics by comparing companies receiving their first US-LP VC investment and those receiving funding from non-US-LP VC investors in the never-US VC subsample with matching on investor size a year before the funding round. Specifically, we include a dummy equal to one if a startup is backed by a large investor, which we define as a non-US VC firm with AUM above the median AUM of US VC firms, as an additional matching variable. We require companies to have been in operation for at least one year prior to the funding round. EBITDA, operating cash, sales, VC round amount, and assets are in millions of real 2025 Swedish krona (SEK). Average Euro and US dollar to SEK exchange rates for December 2025 are 10.895 and 9.294, respectively. When constructing our matched sample, we match jointly on industry (3 bins), stage (3 bins), EBITDA at $t-1$ (quartiles), and number of employees at $t-1$ (quartiles). Section 3 describes the sample construction process in more detail. Panel A shows continuous versions of the variables used for the matching, except for industry. A χ^2-test for differences in the distribution of companies receiving initial US-LP VC and non-US-LP VC funding across industries (using all levels) at $t-1$ is insignificant with a p-value of 0.273. Panel B shows variables used in the analysis but not for the matching, and Panel C shows other variables.

	(1) Full	(2) US-LP VC	(3) Non-US-LP VC	(4) Difference	(5) t-statistic
Panel A: Variables used for matching					
EBITDA (mil SEK)	-3.239	-4.195	-2.880	-1.315	(-0.982)
Employees	5.443	5.684	5.352	0.332	(0.210)
Round number	0.150	0.210	0.127	0.082	(0.940)
Observations	227	62	165	227	
Panel B: Variables used in analysis (but not for matching)					
Operating cash (mil SEK)	-2.960	-4.592	-2.346	-2.246*	(-1.875)
Sales (mil SEK)	6.416	4.936	6.973	-2.037	(-0.699)
Round amount (mil USD)	0.453	0.964	0.261	0.703	(1.125)
Foreign subsidiary dummy	0.062	0.081	0.055	0.026	(0.667)
Observations	227	62	165	227	
Panel C: Other variables					
Assets (mil SEK)	8.455	9.094	8.215	0.879	(0.360)
ROA (%)	-50.735	-55.183	-49.064	-6.119	(-0.511)
Profitable	0.167	0.097	0.194	-0.097**	(-1.989)
VC backed	0.110	0.145	0.097	0.048	(0.951)
Angel backed	0.044	0.065	0.036	0.028	(0.812)
Startup experience of managers	1.616	1.650	1.604	0.046	(0.109)
Same-industry startup exp of mgrs	0.544	0.550	0.542	0.008	(0.051)
VC experience of managers	0.077	0.117	0.062	0.055	(0.706)
USVC experience of managers	0.018	0.017	0.019	-0.002	(-0.094)
Startup experience of directors	2.755	3.665	2.420	1.245**	(2.056)
Same-industry startup exp of dirs	0.765	0.853	0.732	0.121	(0.848)
VC experience of directors	0.267	0.237	0.278	-0.041	(-0.470)
USVC experience of directors	0.031	0.032	0.030	0.002	(0.064)
Observations	227	62	165	227	

Table IA.6
Regression results in experienced and successful VC subsamples

This table presents results for the regressions underlying Figure IA.2 and Figure IA.3. It shows the estimated effects of receiving initial US VC funding on cash from operations, sales, and VC funding in the experienced VC (models 1 to 3) and successful VC (models 4 to 6) subsamples. We define experienced VC as above median VC syndicate funded startups, where syndicate funded startups is the maximum value of VC firm funded startups within a syndicate. We define successful VC as above median VC syndicate performance, where syndicate performance is the maximum value of VC firm performance (fraction of funded startups with an exit) within a syndicate. The unit of analysis is a company-year. Panel A shows results for regressions with a post dummy. For dependent variables in levels, we calculate effect sizes as the US VC × Post coefficient divided by the pre-period average of the dependent variable for the companies receiving US VC funding. For dependent variables in logs, we calculate effect sizes as $e^{USVC \times Post} - 1$. Panel B shows results for regressions with event time dummies. We report p-values from Wald tests for all pre-period US VC × Event time coefficients being jointly equal to zero, which formally tests for the existence of pre-trends between treated and control groups. For brevity, we omit the standalone US VC and Event time dummy coefficients. Standard errors are clustered at the company-cohort level. *t*-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Post dummy						
	Experienced VC subsample			Successful VC subsample		
	(1) Operating cash	(2) Sales (log)	(3) VC funding (log)	(4) Operating cash	(5) Sales (log)	(6) VC funding (log)
US VC × Post	-16.2869***	0.5860**	0.8635***	-11.1298**	0.3255	0.8469***
	(-3.336)	(2.096)	(3.991)	(-2.075)	(1.101)	(3.588)
US VC	-1.3551	-0.3407	0.0305	-3.0007	-0.2859	0.0820
	(-0.361)	(-1.059)	(0.188)	(-0.655)	(-0.817)	(0.438)
Post	-11.1498***	0.9327***	0.4563***	-12.3710***	1.0043***	0.4116***
	(-5.499)	(6.782)	(6.560)	(-4.619)	(6.176)	(5.209)
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,809	1,809	1,809	1,709	1,709	1,709
Adj. R^2	0.098	0.837	0.087	0.080	0.845	0.081
Effect size (%)	144	80	137	70	38	133
Panel B: Event time dummies						
US VC × Event time=-4	8.0669	-0.2085	-0.0113	9.7257	-0.0439	0.0064
	(1.335)	(-0.440)	(-0.033)	(1.441)	(-0.093)	(0.018)
US VC × Event time=-3	8.2296	-0.3021	-0.2540	11.5248*	0.3899	0.2309
	(1.552)	(-0.872)	(-0.835)	(1.883)	(1.054)	(0.595)
US VC × Event time=-2	3.9266	-0.6458**	-0.2246	4.4915	-0.1584	0.1953
	(0.946)	(-1.971)	(-0.793)	(0.845)	(-0.463)	(0.560)
US VC × Event time=0	-1.4373	-0.2391	0.7369***	1.8327	0.0983	1.2693***
	(-0.217)	(-0.888)	(2.809)	(0.240)	(0.353)	(4.533)
US VC × Event time=1	-4.8369	0.0311	0.6756*	-5.0447	-0.0506	0.7759**
	(-0.689)	(0.110)	(1.893)	(-0.603)	(-0.176)	(1.979)
US VC × Event time=2	-9.9889	0.4992	0.8888**	-9.2682	0.4076	1.0375**
	(-1.161)	(1.539)	(2.080)	(-0.959)	(1.084)	(2.245)
US VC × Event time=3	-15.5175	0.5410	0.4077	-13.2934	0.8187**	0.8293*
	(-1.643)	(1.451)	(1.041)	(-1.295)	(2.097)	(1.909)
US VC × Event time=4	-28.9109**	0.3718	1.0932**	-16.6032	0.4971	1.3318***
	(-2.247)	(0.788)	(2.383)	(-1.174)	(1.084)	(2.654)
US VC × Event time=5	-36.2052***	0.6051	1.0322*	-21.7804	0.2977	1.2950**
	(-2.644)	(0.964)	(1.763)	(-1.384)	(0.484)	(2.198)
US VC × Event time=6	-13.4870	1.1384*	0.3810	6.6398	0.2988	0.7496
	(-1.136)	(1.821)	(0.659)	(0.504)	(0.504)	(1.291)
US VC × Event time=7	-6.4267	1.2889	1.2832	15.0733	-1.1601	1.4030**
	(-0.210)	(1.522)	(1.412)	(0.990)	(-1.367)	(2.100)
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,809	1,809	1,809	1,709	1,709	1,709
Adj. R^2	0.109	0.841	0.181	0.088	0.848	0.196
Pre-trends Wald p-val	0.455	0.255	0.759	0.197	0.300	0.892

Table IA.7

Descriptive statistics: First large VC investment as treatment

This table presents descriptive statistics by comparing companies receiving their first large VC investment and those receiving funding from non-large VC investors in the never-US VC subsample a year before the funding round. We define initial large VC as an investment by a non-US VC firm that has above median US VC firm AUM. We require companies to have been in operation for at least one year prior to the funding round. EBITDA, operating cash, sales, VC round amount, and assets are in millions of real 2025 Swedish krona (SEK). Average Euro and US dollar to SEK exchange rates for December 2025 are 10.895 and 9.294, respectively. When constructing our matched sample, we match jointly on industry (3 bins), stage (3 bins), EBITDA at $t-1$ (quartiles), and number of employees at $t-1$ (quartiles). Section 3 describes the sample construction process in more detail. Panel A shows continuous versions of the variables used for the matching, except for industry. A χ^2-test for differences in the distribution of companies receiving initial large VC and non-large VC funding across industries (using all levels) at $t-1$ is insignificant with a p-value of 0.431. Panel B shows variables used in the analysis but not for the matching, and Panel C shows other variables.

	(1) Full	(2) Large VC	(3) Non-large VC	(4) Difference	(5) t-statistic
Panel A: Variables used for matching					
EBITDA (mil SEK)	-9.235	-13.621	-7.652	-5.970	(-1.118)
Employees	16.729	22.042	14.811	7.231	(0.595)
Round number	0.177	0.250	0.150	0.100	(1.415)
Observations	181	48	133	181	
Panel B: Variables used in analysis (but not for matching)					
Operating cash (mil SEK)	-8.242	-11.884	-6.927	-4.957	(-1.003)
Sales (mil SEK)	20.036	32.188	15.650	16.538	(0.732)
Round amount (mil USD)	1.701	2.166	1.533	0.632	(0.420)
Foreign subsidiary dummy	0.088	0.104	0.083	0.021	(0.424)
Observations	181	48	133	181	
Panel C: Other variables					
Assets (mil SEK)	23.038	20.881	23.817	-2.936	(-0.248)
ROA (%)	-52.625	-72.634	-45.404	-27.231*	(-1.924)
Profitable	0.215	0.125	0.248	-0.123**	(-2.013)
VC backed	0.177	0.250	0.150	0.100	(1.415)
Angel backed	0.039	0.042	0.038	0.004	(0.121)
Startup experience of managers	1.481	1.469	1.485	-0.016	(-0.043)
Same-industry startup exp of mgrs	0.444	0.604	0.386	0.218	(1.212)
VC experience of managers	0.114	0.125	0.110	0.015	(0.155)
USVC experience of managers	0.033	0.062	0.023	0.040	(0.614)
Startup experience of directors	2.971	3.125	2.914	0.212	(0.425)
Same-industry startup exp of dirs	0.787	0.792	0.786	0.006	(0.041)
VC experience of directors	0.290	0.369	0.261	0.108	(0.860)
USVC experience of directors	0.055	0.081	0.046	0.035	(0.902)
Observations	181	48	133	181	

Table IA.8
First large VC investment as treatment

This table presents regressions results for the effects of receiving initial large VC funding in the never-US VC subsample underlying Figure IA.4. The dependent variables are cash from operations, sales, and VC funding. We define initial large VC as an investment by a non-US VC firm that has above median US VC firm AUM. The unit of analysis is a company-year. Panel A shows results for regressions with a post dummy. For dependent variables in levels, we calculate effect sizes as the Large VC × Post coefficient divided by the pre-period average of the dependent variable for the companies receiving large VC funding. For dependent variables in logs, we calculate effect sizes as $e^{LargeVC \times Post} - 1$. Panel B shows results for regressions with event time dummies. We report p-values from Wald tests for all pre-period Large VC × Event time coefficients being jointly equal to zero, which formally tests for the existence of pre-trends between treated and control groups. For brevity, we omit the standalone Large VC and Event time dummy coefficients. Table IA.7 describes the sample. Standard errors are clustered at the company-cohort level. *t*-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Post dummy			
	(1) Operating cash	(2) Sales (log)	(3) VC funding (log)
Large VC × Post	-16.7948**	1.1313***	0.8590***
	(-2.348)	(2.950)	(4.284)
Large VC	-2.2497	-0.1418	0.0533
	(-0.514)	(-0.425)	(0.658)
Post	-10.6813***	0.6533***	0.6847***
	(-3.935)	(3.770)	(9.318)
Cohort FE	Yes	Yes	Yes
Observations	1,472	1,472	1,472
Adj. R^2	0.119	0.866	0.136
Effect size (%)	167	210	136
Panel B: Event time dummies			
Large VC × Event time=-4	2.7420	-0.4500	-0.2011
	(0.681)	(-0.830)	(-1.308)
Large VC × Event time=-3	4.0767	-0.7292	-0.0442
	(1.376)	(-1.378)	(-0.180)
Large VC × Event time=-2	1.5609	-0.1260	0.0057
	(0.734)	(-0.363)	(0.025)
Large VC × Event time=0	-4.3416	0.6486**	1.7347***
	(-1.287)	(2.486)	(6.283)
Large VC × Event time=1	-3.7411	0.7395**	0.8304**
	(-0.794)	(2.218)	(2.380)
Large VC × Event time=2	-17.1728*	1.0076***	0.5733
	(-1.876)	(2.628)	(1.429)
Large VC × Event time=3	-26.2090**	1.1671***	0.3964
	(-2.161)	(2.782)	(0.960)
Large VC × Event time=4	-27.0668	0.5194	0.7351
	(-1.613)	(0.734)	(1.420)
Large VC × Event time=5	-13.6716	1.6055***	0.2016
	(-0.838)	(2.835)	(0.373)
Large VC × Event time=6	-27.2975	1.4513*	0.6197
	(-1.044)	(1.792)	(0.962)
Large VC × Event time=7	-43.4465	1.2891	0.0483
	(-1.269)	(1.598)	(0.080)
Cohort FE	Yes	Yes	Yes
Observations	1,472	1,472	1,472
Adj. R^2	0.130	0.869	0.246
Pre-trends Wald p-val	0.593	0.486	0.345

Table IA.9
First large VC investment as treatment: Reinvestments

This table presents regressions results for the effects of receiving initial large VC funding in the never-US VC subsample. The dependent variable is the number of reinvestments by $t = 0$ investors. We define initial large VC as an investment by a non-US VC firm that has above median US VC firm AUM. The unit of analysis is a company-year. Panel A shows results for a regression with a Large VC dummy. We calculate the effect size as the Large VC × Post coefficient divided by post-period average of the dependent variable. Panel B shows results for a regression with Large VC × Event time dummies, with event year zero omitted. For brevity, we omit the standalone Large VC and Event time dummy coefficients. Table IA.7 describes the sample. Standard errors are clustered at the company-cohort level. t-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Large VC dummy	
	(1) Reinvestments
Large VC	0.6398***
	(2.892)
Cohort FE	Yes
Observations	1,136
Adj. R^2	0.088
Effect size (%)	115

Panel B: Event time dummies	
US VC × Event time=1	0.2970**
	(2.117)
US VC × Event time=2	0.5286***
	(2.604)
US VC × Event time=3	0.6000**
	(2.410)
US VC × Event time=4	0.9401**
	(2.212)
US VC × Event time=5	0.9901**
	(2.018)
US VC × Event time=6	0.8502*
	(1.713)
US VC × Event time=7	1.1346*
	(1.860)
Cohort FE	Yes
Observations	1,136
Adj. R^2	0.176
Pre-trends Wald p-val	

Table IA.10

Descriptive statistics: First experienced VC investment as treatment

This table presents descriptive statistics by comparing companies receiving their first experienced VC investment and those receiving funding from non-experienced VC investors in the never-US VC subsample a year before the funding round. We define initial experienced VC as an investment by a non-US VC firm that has above median US VC firm funded startups. We require companies to have been in operation for at least one year prior to the funding round. EBITDA, operating cash, sales, VC round amount, and assets are in millions of real 2025 Swedish krona (SEK). Average Euro and US dollar to SEK exchange rates for December 2025 are 10.895 and 9.294, respectively. When constructing our matched sample, we match jointly on industry (3 bins), stage (3 bins), EBITDA at $t-1$ (quartiles), and number of employees at $t-1$ (quartiles). Section 3 describes the sample construction process in more detail. Panel A shows continuous versions of the variables used for the matching, except for industry. A χ^2-test for differences in the distribution of companies receiving initial experienced VC and non-experienced VC funding across industries (using all levels) at $t-1$ is insignificant with a p-value of 0.379. Panel B shows variables used in the analysis but not for the matching, and Panel C shows other variables.

	(1) Full	(2) Experienced VC	(3) Non-experienced VC	(4) Difference	(5) t-statistic
Panel A: Variables used for matching					
EBITDA (mil SEK)	-3.386	-3.396	-3.378	-0.018	(-0.022)
Employees	6.700	6.282	7.051	-0.768	(-0.683)
Round number	0.141	0.143	0.140	0.003	(0.083)
Observations	919	420	499	919	
Panel B: Variables used in analysis (but not for matching)					
Operating cash (mil SEK)	-3.211	-3.361	-3.085	-0.276	(-0.322)
Sales (mil SEK)	11.701	10.879	12.393	-1.514	(-0.427)
Round amount (mil USD)	1.250	0.700	1.714	-1.014	(-1.173)
Foreign subsidiary dummy	0.055	0.050	0.060	-0.010	(-0.672)
Observations	919	420	499	919	
Panel C: Other variables					
Assets (mil SEK)	15.930	14.929	16.773	-1.845	(-0.479)
ROA (%)	-44.046	-43.722	-44.318	0.596	(0.115)
Profitable	0.223	0.233	0.214	0.019	(0.683)
VC backed	0.108	0.105	0.110	-0.005	(-0.266)
Angel backed	0.041	0.026	0.054	-0.028**	(-2.182)
Startup experience of managers	1.251	1.280	1.227	0.053	(0.371)
Same-industry startup exp of mgrs	0.372	0.381	0.364	0.017	(0.291)
VC experience of managers	0.065	0.104	0.032	0.071**	(2.213)
USVC experience of managers	0.011	0.017	0.006	0.011	(0.937)
Startup experience of directors	2.776	2.814	2.743	0.072	(0.378)
Same-industry startup exp of dirs	0.686	0.737	0.643	0.094	(1.436)
VC experience of directors	0.198	0.260	0.146	0.114***	(3.137)
USVC experience of directors	0.028	0.037	0.021	0.016	(1.424)
Observations	919	420	499	919	

Table IA.11
First experienced VC investment as treatment

This table presents regressions results for the effects of receiving initial experienced VC funding in the never-US VC subsample underlying Figure IA.6. The dependent variables are cash from operations, sales, and VC funding. We define initial experienced VC as an investment by a non-US VC firm that has above median US VC firm funded startups. The unit of analysis is a company-year. Panel A shows results for regressions with a post dummy. For dependent variables in levels, we calculate effect sizes as the Experienced VC × Post coefficient divided by the pre-period average of the dependent variable for the companies receiving experienced VC funding. For dependent variables in logs, we calculate effect sizes as $e^{ExperiencedVC \times Post} - 1$. Panel B shows results for regressions with event time dummies. We report p-values from Wald tests for all pre-period Experienced VC × Event time coefficients being jointly equal to zero, which formally tests for the existence of pre-trends between treated and control groups. For brevity, we omit the standalone Experienced VC and Event time dummy coefficients. Table IA.10 describes the sample. Standard errors are clustered at the company-cohort level. *t*-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Post dummy			
	(1) Operating cash	(2) Sales (log)	(3) VC funding (log)
Experienced VC × Post	1.1789	0.0585	0.1512***
	(1.142)	(0.429)	(2.733)
Experienced VC	-0.6911	-0.3861***	0.0066
	(-0.851)	(-2.923)	(0.207)
Post	-6.2803***	0.7597***	0.5080***
	(-8.322)	(8.220)	(14.766)
Cohort FE	Yes	Yes	Yes
Observations	7,471	7,471	7,471
Adj. R^2	0.040	0.859	0.073
Effect size (%)	-39	6	16

Panel B: Event time dummies			
Experienced VC × Event time=-4	-1.1478	-0.2522	0.1026*
	(-1.416)	(-1.214)	(1.674)
Experienced VC × Event time=-3	-1.1351	-0.2551	0.0585
	(-1.481)	(-1.452)	(1.076)
Experienced VC × Event time=-2	0.5677	0.1266	0.0634
	(0.688)	(0.848)	(1.053)
Experienced VC × Event time=0	0.6593	-0.0852	0.4170***
	(0.699)	(-0.694)	(4.118)
Experienced VC × Event time=1	0.3373	0.0373	0.1952**
	(0.274)	(0.279)	(2.292)
Experienced VC × Event time=2	1.8784	0.1601	0.0680
	(1.408)	(1.033)	(0.670)
Experienced VC × Event time=3	1.4847	0.0415	0.2814***
	(0.977)	(0.243)	(2.842)
Experienced VC × Event time=4	0.4080	-0.2572	0.1415
	(0.212)	(-1.255)	(1.351)
Experienced VC × Event time=5	1.2754	-0.0676	0.0683
	(0.598)	(-0.296)	(0.573)
Experienced VC × Event time=6	1.2740	-0.0705	0.1753*
	(0.535)	(-0.269)	(1.675)
Experienced VC × Event time=7	0.1834	0.1244	0.1446
	(0.062)	(0.391)	(1.128)
Cohort FE	Yes	Yes	Yes
Observations	7,471	7,471	7,471
Adj. R^2	0.041	0.862	0.184
Pre-trends Wald p-val	0.110	0.085	0.407

Table IA.12

Descriptive statistics: First successful VC investment as treatment

This table presents descriptive statistics by comparing companies receiving their first successful VC investment and those receiving funding from non-successful VC investors in the never-US VC subsample a year before the funding round. We define initial successful VC as an investment by a non-US VC firm that has above median US VC firm performance, where performance is the fraction of funded startups with an exit. We require companies to have been in operation for at least one year prior to the funding round. EBITDA, operating cash, sales, VC round amount, and assets are in millions of real 2025 Swedish krona (SEK). Average Euro and US dollar to SEK exchange rates for December 2025 are 10.895 and 9.294, respectively. When constructing our matched sample, we match jointly on industry (3 bins), stage (3 bins), EBITDA at $t-1$ (quartiles), and number of employees at $t-1$ (quartiles). Section 3 describes the sample construction process in more detail. Panel A shows continuous versions of the variables used for the matching, except for industry. A χ^2-test for differences in the distribution of companies receiving initial successful VC and non-successful VC funding across industries (using all levels) at $t-1$ is insignificant with a p-value of 0.340. Panel B shows variables used in the analysis but not for the matching, and Panel C shows other variables.

	(1) Full	(2) Successful VC	(3) Non-successful VC	(4) Difference	(5) t-statistic
Panel A: Variables used for matching					
EBITDA (mil SEK)	-2.836	-2.950	-2.744	-0.206	(-0.304)
Employees	6.822	6.698	6.922	-0.224	(-0.216)
Round number	0.131	0.124	0.137	-0.013	(-0.489)
Observations	921	411	510	921	
Panel B: Variables used in analysis (but not for matching)					
Operating cash (mil SEK)	-2.428	-2.034	-2.745	0.711	(0.995)
Sales (mil SEK)	10.406	11.597	9.446	2.151	(0.805)
Round amount (mil USD)	1.112	0.644	1.489	-0.844	(-1.154)
Foreign subsidiary dummy	0.058	0.061	0.055	0.006	(0.381)
Observations	921	411	510	921	
Panel C: Other variables					
Assets (mil SEK)	13.447	14.025	12.980	1.045	(0.348)
ROA (%)	-43.303	-45.348	-41.656	-3.692	(-0.699)
Profitable	0.227	0.238	0.218	0.021	(0.746)
VC backed	0.109	0.102	0.114	-0.012	(-0.562)
Angel backed	0.046	0.036	0.053	-0.016	(-1.211)
Startup experience of managers	1.306	1.309	1.304	0.006	(0.039)
Same-industry startup exp of mgrs	0.375	0.385	0.367	0.018	(0.299)
VC experience of managers	0.062	0.083	0.045	0.038	(1.104)
USVC experience of managers	0.010	0.015	0.006	0.009	(0.776)
Startup experience of directors	2.794	2.866	2.736	0.130	(0.695)
Same-industry startup exp of dirs	0.694	0.787	0.618	0.169**	(2.514)
VC experience of directors	0.200	0.267	0.146	0.122***	(3.298)
USVC experience of directors	0.026	0.036	0.018	0.018*	(1.655)
Observations	921	411	510	921	

Table IA.13
First successful VC investment as treatment

This table presents regressions results for the effects of receiving initial successful VC funding in the never-US VC sub-sample underlying Figure IA.7. The dependent variables are cash from operations, sales, and VC funding. We define initial successful VC as an investment by a non-US VC firm that has above median US VC firm performance, where performance is the fraction of funded startups with an exit. The unit of analysis is a company-year. Panel A shows results for regressions with a post dummy. For dependent variables in levels, we calculate effect sizes as the Successful VC × Post coefficient divided by the pre-period average of the dependent variable for the companies receiving successful VC funding. For dependent variables in logs, we calculate effect sizes as $e^{SuccessfulVC \times Post} - 1$. Panel B shows results for regressions with event time dummies. We report p-values from Wald tests for all pre-period Successful VC × Event time coefficients being jointly equal to zero, which formally tests for the existence of pre-trends between treated and control groups. For brevity, we omit the standalone Successful VC and Event time dummy coefficients. Table IA.12 describes the sample. Standard errors are clustered at the company-cohort level. *t*-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Operating cash	(2) Sales (log)	(3) VC funding (log)
Panel A: Post dummy			
Successful VC × Post	-1.1127	0.1109	0.1918***
	(-1.137)	(0.834)	(3.646)
Successful VC	0.6465	-0.0652	-0.0421*
	(1.143)	(-0.499)	(-1.779)
Post	-5.3460***	0.7498***	0.4798***
	(-7.820)	(8.428)	(14.194)
Cohort FE	Yes	Yes	Yes
Observations	7,563	7,563	7,563
Adj. R^2	0.040	0.867	0.066
Effect size (%)	59	12	21
Panel B: Event time dummies			
Successful VC × Event time=-4	0.3075	0.1439	-0.0198
	(0.310)	(0.705)	(-0.342)
Successful VC × Event time=-3	-1.1966	-0.1772	0.0797*
	(-1.336)	(-0.988)	(1.708)
Successful VC × Event time=-2	-0.2876	-0.0349	0.0285
	(-0.346)	(-0.226)	(0.510)
Successful VC × Event time=0	-1.9932**	-0.0324	0.4594***
	(-2.114)	(-0.267)	(4.527)
Successful VC × Event time=1	-1.3107	0.0442	0.1399*
	(-1.135)	(0.339)	(1.653)
Successful VC × Event time=2	1.3514	0.1072	0.0121
	(1.093)	(0.686)	(0.123)
Successful VC × Event time=3	-1.3653	-0.0286	0.3133***
	(-0.915)	(-0.166)	(3.200)
Successful VC × Event time=4	-2.5246	0.1849	0.0934
	(-1.385)	(0.930)	(0.879)
Successful VC × Event time=5	-1.4798	0.3157	0.1458
	(-0.677)	(1.468)	(1.257)
Successful VC × Event time=6	-0.2878	0.1659	0.2245**
	(-0.120)	(0.640)	(2.243)
Successful VC × Event time=7	-6.7765**	0.2524	0.2956**
	(-2.227)	(0.833)	(2.136)
Cohort FE	Yes	Yes	Yes
Observations	7,563	7,563	7,563
Adj. R^2	0.043	0.869	0.188
Pre-trends Wald p-val	0.090	0.280	0.242

Table IA.14
Descriptive statistics: First foreign VC investment as treatment

This table presents descriptive statistics by comparing companies receiving their first foreign VC investment and those receiving funding from non-foreign VC investors in the never-US VC subsample a year before the funding round. We require companies to have been in operation for at least one year prior to the funding round. EBITDA, operating cash, sales, VC round amount, and assets are in millions of real 2025 Swedish krona (SEK). Average Euro and US dollar to SEK exchange rates for December 2025 are 10.895 and 9.294, respectively. When constructing our matched sample, we match jointly on industry (3 bins), stage (3 bins), EBITDA at $t-1$ (quartiles), and number of employees at $t-1$ (quartiles). Section 3 describes the sample construction process in more detail. Panel A shows continuous versions of the variables used for the matching, except for industry. A χ^2-test for differences in the distribution of companies receiving initial foreign VC and non-foreign VC funding across industries (using all levels) at $t-1$ is insignificant with a p-value of 0.888. Panel B shows variables used in the analysis but not for the matching, and Panel C shows other variables.

	(1) Full	(2) Foreign VC	(3) Non-foreign VC	(4) Difference	(5) t-statistic
Panel A: Variables used for matching					
EBITDA (mil SEK)	-6.504	-6.318	-6.584	0.266	(0.199)
Employees	10.456	10.195	10.569	-0.374	(-0.154)
VC round number	0.317	0.342	0.306	0.037	(0.538)
Observations	609	184	425	609	
Panel B: Variables used in analysis (but not for matching)					
Operating cash (mil SEK)	-6.245	-5.442	-6.593	1.151	(0.811)
Sales (mil SEK)	13.442	12.872	13.688	-0.817	(-0.151)
VC round amount (mil SEK)	2.466	1.547	2.863	-1.316	(-0.934)
Foreign subsidiary dummy	0.099	0.141	0.080	0.061**	(2.119)
Observations	609	184	425	609	
Panel C: Other variables					
Assets (mil SEK)	17.784	14.073	19.390	-5.317	(-1.211)
ROA (%)	-54.045	-67.433	-48.249	-19.184**	(-2.268)
Profitable	0.190	0.179	0.195	-0.016	(-0.465)
VC backed	0.207	0.223	0.200	0.023	(0.627)
Angel backed	0.044	0.054	0.040	0.014	(0.744)
Startup experience of managers	1.339	1.122	1.433	-0.311*	(-1.761)
Same-industry startup exp of mgrs	0.443	0.439	0.445	-0.006	(-0.076)
VC experience of managers	0.055	0.072	0.048	0.024	(0.858)
USVC experience of managers	0.012	0.017	0.010	0.007	(0.625)
Startup experience of directors	2.854	2.624	2.954	-0.330	(-1.458)
Same-industry startup exp of dirs	0.764	0.771	0.761	0.011	(0.126)
VC experience of directors	0.285	0.296	0.280	0.017	(0.293)
USVC experience of directors	0.037	0.042	0.034	0.008	(0.585)
Observations	609	184	425	609	

Table IA.15
First foreign VC investment as treatment

This table presents regressions results for the effects of receiving initial foreign VC funding in the never-US VC subsample underlying Figure IA.8. The dependent variables are cash from operations, sales, and VC funding. The unit of analysis is a company-year. Panel A shows results for regressions with a post dummy. For dependent variables in levels, we calculate effect sizes as the Foreign VC × Post coefficient divided by the pre-period average of the dependent variable for the companies receiving foreign VC funding. For dependent variables in logs, we calculate effect sizes as $e^{ForeignVC \times Post} - 1$. Panel B shows results for regressions with event time dummies. We report p-values from Wald tests for all pre-period Foreign VC × Event time coefficients being jointly equal to zero, which formally tests for the existence of pre-trends between treated and control groups. For brevity, we omit the standalone Foreign VC and Event time dummy coefficients. Table IA.14 describes the sample. Standard errors are clustered at the company-cohort level. *t*-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Post dummy

	(1) Operating cash	(2) Sales (log)	(3) VC funding (log)
Foreign VC × Post	-1.4530	0.6863***	0.3098***
	(-0.791)	(3.700)	(3.589)
Foreign VC	0.7862	-0.2766	-0.0232
	(0.649)	(-1.634)	(-0.481)
Post	-7.0785***	0.6543***	0.5643***
	(-6.559)	(6.926)	(13.216)
Cohort FE	Yes	Yes	Yes
Observations	4,793	4,793	4,793
Adj. R^2	0.045	0.868	0.072
Effect size (%)	31	99	36

Panel B: Event time dummies

	(1) Operating cash	(2) Sales (log)	(3) VC funding (log)
Foreign VC × Event time=-4	-2.9193**	-0.2391	-0.0865
	(-1.986)	(-0.887)	(-0.924)
Foreign VC × Event time=-3	-0.8387	-0.6697***	0.0563
	(-0.783)	(-2.601)	(0.446)
Foreign VC × Event time=-2	-0.3026	-0.3511*	-0.1243
	(-0.245)	(-1.775)	(-1.085)
Foreign VC × Event time=0	-1.0021	0.2098	0.7302***
	(-0.584)	(1.308)	(4.873)
Foreign VC × Event time=1	-0.4128	0.3080*	0.0770
	(-0.225)	(1.760)	(0.546)
Foreign VC × Event time=2	-2.6925	0.4436**	0.2454
	(-1.020)	(2.123)	(1.441)
Foreign VC × Event time=3	-3.7353	0.4987**	0.3482*
	(-1.322)	(2.187)	(1.948)
Foreign VC × Event time=4	-3.0623	0.4773	-0.0353
	(-0.809)	(1.565)	(-0.211)
Foreign VC × Event time=5	0.7042	0.8985***	-0.1403
	(0.143)	(2.923)	(-0.788)
Foreign VC × Event time=6	-4.1629	0.7250*	0.3843
	(-0.722)	(1.819)	(1.643)
Foreign VC × Event time=7	-8.5686	0.3935	-0.0029
	(-1.129)	(0.805)	(-0.012)
Cohort FE	Yes	Yes	Yes
Observations	4,793	4,793	4,793
Adj. R^2	0.044	0.871	0.195
Pre-trends Wald p-val	0.211	0.058	0.421

Table IA.16
Burn rate and runway

This table presents results for cross-sectional regressions comparing burn rate and runway measures for companies receiving initial US VC funding with those that do not. Runway measures the number of post-period years until a company's next VC round, whereas burn rate measures the average annual cash used by a company until its next VC round. The unit of analysis is a company. Standard errors are clustered at the company-cohort level. t-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Burn rate	(2) Runway
US VC	27.2543***	-1.3632***
	(2.730)	(-4.153)
Cohort FEs	Yes	Yes
Observations	489	489
Adj. R^2	0.013	0.049

Table IA.17
J-curve depth and width

This table presents results for cross-sectional regressions comparing J-curve depth and width measures for companies receiving initial US VC funding with those that do not. Depth measures the maximum losses of a company during the post-period, whereas width measures the number of post-period years a company takes to return to its $t = -1$ level. The unit of analysis is a company. Standard errors are clustered at the company-cohort level. t-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Depth	(2) Width
US VC	-26.2636***	0.6859**
	(-3.711)	(1.966)
Cohort FEs	Yes	Yes
Observations	489	489
Adj. R^2	0.040	0.042

Table IA.18
Alternative measures of outcome variables

This table presents regressions results for the effects of receiving initial US VC funding underlying Figure IA.9. The dependent variables are EBITDA, foreign presence, exit, and VC follow-on funding rounds. We define foreign presence as a dummy equaling one if a company has at least one foreign subsidiary. We define exit as a dummy equaling one, and staying one, once a company has an IPO or acquisition. The unit of analysis is a company-year. The regressions in models (3) and (4) use post-period observations only. Panel A shows results for regressions with a post dummy. For dependent variables in levels, we calculate effect sizes as the US VC × Post coefficient divided by the pre-period average of the dependent variable for the companies receiving US VC funding. For dependent variables in logs, we calculate effect sizes as $e^{USVC \times Post} - 1$. Panel B shows results for regressions with event time dummies. We report p-values from Wald tests for all pre-period US VC × Event time coefficients being jointly equal to zero, which formally tests for the existence of pre-trends between treated and control groups. For brevity, we omit the standalone US VC and Event time dummy coefficients. Table 1 describes the sample. Standard errors are clustered at the company-cohort level. *t*-statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Post dummy				
	(1) EBITDA	(2) Foreign presence	(3) Exit	(4) VC follow-on rounds
US VC × Post	-14.2196***	0.1537***		
	(-3.840)	(4.081)		
US VC	-0.7655	-0.0511	0.0063	0.4345***
	(-0.343)	(-1.548)	(0.238)	(5.050)
Post	-5.7366***	0.0423**		
	(-4.355)	(2.485)		
Cohort FE	Yes	Yes	Yes	Yes
Observations	3,900	3,900	3,003	3,003
Adj. R^2	0.069	0.074	0.047	0.087
Effect size (%)	131	143	5	74
Panel B: Event time dummies				
US VC × Event time=-4	0.2581	-0.0448		
	(0.083)	(-0.965)		
US VC × Event time=-3	1.8799	-0.0274		
	(0.793)	(-0.742)		
US VC × Event time=-2	2.2262	-0.0096		
	(1.318)	(-0.451)		
US VC × Event time=0	-5.4939**	0.0233		
	(-2.128)	(0.940)		
US VC × Event time=1	-7.3733*	0.0850**	-0.0065	0.1160**
	(-1.962)	(2.190)	(-0.343)	(2.408)
US VC × Event time=2	-10.0890**	0.1191**	-0.0197	0.2631***
	(-2.229)	(2.549)	(-0.663)	(3.513)
US VC × Event time=3	-19.9056***	0.1956***	-0.0295	0.3923***
	(-3.344)	(3.863)	(-0.833)	(3.973)
US VC × Event time=4	-24.7053***	0.2372***	0.0025	0.6002***
	(-3.405)	(3.970)	(0.054)	(4.622)
US VC × Event time=5	-20.7242***	0.1901***	0.0437	0.7991***
	(-2.651)	(2.890)	(0.761)	(4.726)
US VC × Event time=6	-13.0682**	0.2279***	0.1284*	0.8884***
	(-1.967)	(2.850)	(1.927)	(4.349)
US VC × Event time=7	-15.7233*	0.3193***	0.1639**	1.0498***
	(-1.659)	(2.972)	(2.057)	(4.301)
Cohort FE	Yes	Yes	Yes	Yes
Observations	3,900	3,900	3,003	3,003
Adj. R^2	0.077	0.078	0.143	0.249
Pre-trends Wald p-val	0.446	0.811		