Venture Capital Networks and Cross-Border Startup Knowledge Spillovers *

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Abstract

Venture capital (VC) networks facilitate reverse knowledge spillovers from U.S. investments in foreign startups back to the United States. Using the first U.S. VC deal in a foreign company as a quasi-exogenous shock in a difference-in-differences design, I show that investees' pre-existing patents become 18% more likely to be cited by U.S. entities, with no corresponding change in citations from other countries. Spillovers are concentrated among US startups most closely connected to the investing VC through its network of prior syndication ties, while geographically proximate firms show no such effects. A similar design applied to domestic coast-to-coast VC deals confirms that the network channel is especially salient in cross-border settings. These knowledge flows translate into real outcomes: patent output rises by 10% overall and 22% in investee-related technologies; high-quality innovation increases by 10% overall and 34% in related technologies. Closely connected firms are also more likely to achieve successful exits through IPO or acquisition. The findings indicate that VCs transmit startup knowledge across borders through their syndication networks, enhancing innovation and performance beyond their direct portfolios.

Keywords: Innovation, Investor Network, Knowledge Spillover, Venture Capital

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1 Introduction

U.S. venture capital (VC) finances a small share of startups yet disproportionately backs highly innovative firms, playing a central role in the U.S. innovation ecosystem (Lerner and Nanda, 2020). Two features distinguish VC: active involvement in portfolio companies and reliance on extensive investment networks. VCs typically acquire sizable equity stakes—about 20% at the median—conferring governance rights and fostering close engagement with startups (Gompers et al., 2020). These interactions deepen investors' understanding of portfolio technologies and enhance their capacity to absorb and transmit knowledge. At the same time, the industry is highly networked: past investment syndication network has been shown to be crucial for deal sourcing and subsequent portfolio performance (Hochberg et al., 2007). The coexistence of these features suggests that VC networks may serve as an important channel for transmitting knowledge. Prior research documents knowledge flows within direct portfolio relationships (González-Uribe, 2020; Eldar and Grennan, 2024). This paper extends that literature by examining whether VCs generate spillovers *beyond* their own portfolios—through networks formed via past syndication—and whether these spillovers affect the innovation and performance of connected, non-portfolio companies.

U.S. VC activity, once concentrated domestically, has become increasingly global since the early 2000s. According to PitchBook (the leading source of VC activities), the share of cross-border deals by U.S. investors rose from roughly 10% in 2000 to over 30% in 2022, underscoring the need to understand how VC shapes international knowledge flows. Startup knowledge is particularly opaque and less likely to traverse borders than knowledge generated by multinationals with foreign affiliates or established trade links, making the cross-border transmission of startup ideas both important and nontrivial. Historically, limited cross-border VC activity and the absence of detailed deal-level data hindered systematic analysis. This paper fills that gap by examining U.S. VCs' cross-border investments in foreign startups with deal-level data from Pitchbook, and showing how their prior syndication networks channel knowledge from investees back into the U.S. innovation ecosystem.

A concrete example illustrates how foreign startup knowledge can diffuse to the United States through VC syndication networks.[1] In 2005, the U.S. venture firm Alta Partners made an early U.S. investment in Swedish Orphan Biovitrum (then Biovitrum). While developing serotonergic candidates, Biovitrum patented an "oxygen-bridge" construction method for joining heteroaromatic rings (USPTO Patent 7534794). In 2008, the U.S. startup Array BioPharma cited and reused this bridge-building step to assemble glucokinase activators for blood-glucose control (USPTO Patent 8212045)— a foreign, method-level innovation enabled a U.S., product-level advance in a different program. Crucially, Array was not just any U.S. firm; it sat within Alta Partners' prior syndication network: Alta had co-invested with Array's direct investors, including Boulder Ventures (2000) and Synthesis Capital (2003). Based on United States Patent and Trademark Office (USPTO) records, Array was the first U.S. assignee to cite the Biovitrum patent; the next U.S. citation in USPTO data did not appear until 2014. The timing and network positioning are suggestive of early adoption flowing along the investing VC's syndication ties, with broader diffusion arriving later.

To formally test how VCs foster cross-border startup knowledge flows, I proceed in three steps. First, I examine aggregate flows by testing whether U.S. entities become more likely to cite a foreign investee's pre-existing patents after its initial U.S. VC deal. Second, I assess the role of VC syndication networks by asking whether effects are stronger along closer ties; I contrast network proximity with geographic proximity and benchmark against domestic coast-to-coast investments to show that networks matter especially in cross-border settings. Third, I study U.S. firm-level outcomes, documenting increases in patent output and quality, particularly in investee-related technologies, and showing that closely connected firms expand inventor participation and are more likely to exit via IPO or acquisition.

I begin with the aggregate analysis and test whether U.S. entities cite a foreign investee's patents more often following the investee's *first* U.S. VC deal. I treat this initial investment as a quasi-exogenous shock to citations of the investee's *pre-existing* patents, which by

[1] Based on PitchBook sources and USPTO patent documents

definition could not have been influenced by U.S. VCs. Treated patents are matched to control patents with similar observable characteristics, and I estimate a difference-in-differences specification to assess whether U.S. citation incidence rises after the investment. Two endogeneity concerns remain: VCs may select higher-quality firms based on unobservables, and they may target technologies that align with future U.S. demand. To probe the first concern, I (i) run a placebo using citations from third countries (neither the United States nor the investee's home country) and (ii) estimate a triple-differences contrast that directly compares the U.S. DID with the third-country DID. The placebo shows no effect, and the triple-differences estimate is positive, significant, and similar in magnitude to the main U.S. DID, reducing concerns about selection on quality. I address the second concern through the next section on channels. Overall, the first U.S. VC investment increases the annual probability that a foreign patent receives a U.S. citation by 3.51 percentage points—an 18.6% increase relative to the 18.9 percentage-point pre-treat mean of the treated.

To examine transmission channels, in particular, the role of VC syndication networks, I test whether spillover intensity varies with U.S. entities' network proximity to the investing VC. Proximity is defined by past deal syndication: firms linked to the VC's direct co-investors are second-degree, those linked via co-investors' co-investors are third-degree, and all others are fourth-degree. Shared portfolio companies of the investing VC and the foreign investee are excluded to avoid reverse-causality and selection concerns, and all network links are fixed prior to the cross-border deal. Each citing patent inherits the network tier of its assignee. To avoid confounding proximity with industry or location composition across network tiers, I define for each treated patent a citation risk set of U.S. patents whose assignees have revealed demand for closely related technologies—U.S. patents that cite other foreign patents matching the treated patent's country, CPC subclass, and application year.[2] Conditional on citing within this risk set, I test whether closer-connected firms experience a larger post-investment increase in the probability of citing the specific treated patent,

[2] "CPC subclass" refers to the four-character subclass level (e.g., H04L) in the Cooperative Patent Classification system used by the United States Patent and Trademark Office (USPTO)

controlling for the citing patent's location and technology class to absorb peer effects and information clustering. This design aligns comparisons within a common technological and geographic space, isolating the contribution of network proximity.

Results show that pre-investment, conditional citation rates do not differ significantly across network tiers. Post-investment, however, patents filed by the second-degree (closest) connections exhibit a 2.6 percentage-point higher conditional likelihood of citing the treated patent relative to the least connected group (pre-treatment mean =2.83 pp), while more distant connections do not differ from one another. This pattern highlights the role of syndication proximity in driving cross-border spillovers and also addresses the second concern in the above aggregate analysis that U.S. VCs simply select technologies aligned with future domestic demand. After controlling for patent-subclass $\times$ city $\times$ year trend, the increase appears only among firms closely tied to the investing VC. This pattern is inconsistent with predictive alignment or correlated investment choices between the investing VC and aggregate U.S. demand and instead points to transmission through the VC network.

I benchmark the syndication-network channel with two tests: (i) an alternative channel based on geographic proximity, a prevalent conduit for knowledge flow, and (ii) a domestic benchmark that assesses whether syndication networks similarly transmit knowledge within the United States. Applying the same framework, I find that U.S. patents whose assignees are located in the same city as the investing VC do not exhibit a larger post-investment change in conditional citation likelihood. Thus, cross-border spillovers do not diffuse broadly to geographically proximate entities; instead, they travel along investment networks. Although VC networks need not operate only across borders, domestic knowledge flows arise more readily through alternative channels—geographic proximity, labor mobility, and social ties (Agrawal et al., 2006)—which may reduce the marginal role of VC syndication ties. To test this, I examine East Coast VCs' initial investments in West Coast companies and ask whether East Coast firms with closer prior ties to the investor differentially cite the investee's prior patents. The results show no significant post-investment differences across network tiers, suggesting that the syndication channel is especially salient in the cross-border context, where other diffusion pathways are more constrained.

I complement the citation analysis with firm-level tests, tracking changes in the quantity and quality of patenting overall and in investee-related fields. Because patent production is where external ideas are assimilated and recombined, increases in output and quality indicate that recipients have internalized foreign knowledge into new inventions. Building on the finding that spillovers concentrate among second-degree connections, I implement a firm-level staggered difference-in-differences design that, for each investor×deal year, compares pre- versus post-investment outcomes for second- versus third-degree connected firms, using the latter as a close control. Innovation is measured along two dimensions—quantity (patent counts) and quality (forward citations and the Kelly et al. (2021) importance metric)—and the specification includes tight fixed effects that absorb firms' past patenting behavior, detailed industry-by-time variation, and location-based innovation trends. In addition, I examine inventor participation—the annual count of unique inventors on a firm's patents[3]. If VC networks transmit knowledge and raise innovation productivity, closely connected U.S. firms is likely to broaden their inventor base.

The results indicate that VC-induced spillovers raise patent output among closely connected firms by approximately 10.5%, with high-quality output increasing by a similar 9.9%. Effects are larger within the "invested classes"—patent classes overlapping the foreign investee's technologies—where total output rises by 22.3% and high-quality output by 34.5%. These findings indicate that VC-induced spillovers materially improve both the productivity and quality of innovation among firms closely connected through the VC's past syndication network, with the largest gains concentrated in technologies directly related to the foreign investees. Moreover, the number of unique inventors rises by 10.4% overall and by 21.3% within the invested classes, suggesting that these network-connected firms expand their in-

[3]In the absence of comprehensive firm-level employment data—especially for startups—I observe contributing inventors only. Participation does not necessarily imply employment; inventors may contribute via outsourcing or part-time collaborations. I therefore interpret changes in inventor counts as shifts in the firm's innovation resource pool, not in headcount.

novative efforts by engaging a broader pool of inventors.

Lastly, I examine whether knowledge spillovers affect firm performance, measured by a success indicator equal to one if a connected U.S. startup exits via M&A or IPO within five years of the VC's cross-border investment and zero otherwise.[4] Mirroring the innovation analysis, I compare five-year exit outcomes for second- versus third-degree connections to the investing VC. Specifically, within each investor $\times$ deal-year cohort, I compute differences in five-year success rates between second- and third-degree firms following the foreign investment. The specification includes tight fixed effects interacting cohort with a firm's initial VC deal year, initial deal type, and industry, and additionally controls for each firm's direct VC investor with investor fixed effects to absorb style/quality differences in backing VCs. The results show a 1.3 percentage-point higher likelihood in success for second-degree (close) connections—about 5% relative to the sample baseline exit rate of 25.5 percentage points. As a placebo, I repeat the comparison over the five years prior to the cross-border investment; the differences are statistically insignificant, indicating no pre-existing gap after conditioning on observables. Taken together, the evidence suggests that U.S. VCs' cross-border knowledge spillovers not only raise innovative activity but also increase the likelihood of successful exits among closely connected startups.

This paper contributes to two main strands of literature. The first is the literature on venture capital and innovation. Prior research has shown that venture capital plays an important role in shaping the innovation outcomes and information exchange of their portfolio companies (Chemmanur et al., 2011; Tian and Wang, 2014; Bernstein et al., 2016; González-Uribe, 2020; Eldar and Grennan, 2024). This paper extends this literature by showing that the influence of VCs on innovation extends beyond the boundaries of their portfolio companies: the knowledge spillovers they foster affect both the quality of innovation and the firm value of companies connected through their investment networks, even in the absence of direct involvement. Moreover, VC networks have been shown to be crucial for

[4]Results are robust to alternative event windows.

investment decisions such as deal sourcing and investment performance (Hochberg et al., 2007; Gompers et al., 2020). The findings of this paper demonstrate that VC investor networks are not only central to investment decisions and performance but also serve as an important channel of knowledge flow.

The second strand of related work is the literature on knowledge spillovers. Prior studies document spillovers across a variety of settings and channels (Singh, 2005; Ellison et al., 2010; Keller and Yeaple, 2013; Liu and Ma, 2021; Atkin et al., 2022; Aghion et al., 2023). This paper examines cross-border spillovers of startup technology transmitted through investments by *independent* venture capital firms. Because VC-backed innovation is, on average, higher quality (Lerner and Nanda, 2020) and traditional diffusion channels are more constrained internationally, VC networks provide a particularly powerful conduit for startup knowledge. The evidence further shows that these spillovers are selective: they accrue not to geographically proximate firms broadly, but to firms with established ties to the investing VC. Related work by Akcigit et al. (2024) analyzes reverse knowledge flows at the macro level via cross-border corporate venture capital (CVC), where large corporations invest in high-acquisition-potential startups and absorb their technologies through strategic and operational synergies (Benson and Ziedonis, 2010; Chemmanur et al., 2014; Ma, 2020). In contrast, this paper focuses on independent venture-capital funds—pure financial intermediaries that cannot directly exploit portfolio technologies—and shows how their syndication networks transmit knowledge, shaping firm-level innovation beyond the funds' own portfolios.

The paper proceeds as follows. Section 2 describes the data and key measures. Section 3 presents citation-based evidence of aggregate spillovers and identifies the role of VCs' past syndication networks. Section 4 provides firm-level evidence and evaluates impacts on connected U.S. firms. Section 5 reports robustness checks. Section 6 concludes.

2 Data and Key Measurements

I focus on international investments made by U.S.-headquartered venture capital (VC) firms in portfolio companies between 2000 and 2017.[5] The study draws on two primary data sources. Investment holdings, characteristics of all VC-backed startups, and firm exit outcomes are obtained from PitchBook. Patent applications, technology classifications, locations, and inventor-level information are taken from USPTO records provided by PatentsView.

2.1 U.S. Venture Capital International Holdings Data

I use PitchBook's Global dataset to identify venture investments initiated by U.S.-headquartered VC firms. To ensure data quality, the sample begins in 2000. I focus on traditional VC-stage financing by non-corporate investors, retaining deals categorized as "Seed," "Early Stage VC," or "Late Stage VC," and excluding transactions for which the primary investor type is "Corporate VC" or "Corporation," thereby removing corporate venture capital activity.

Foreign investments are defined using PitchBook's location data: a U.S. VC's location is the headquarters of the management firm (e.g., Sequoia Capital is classified as U.S.-based in this dataset).[6] I restrict the sample to deals in which U.S. VCs invest in companies headquartered outside the United States during the sample period. For each foreign portfolio company, I retain only the first VC deal involving a U.S. investor and exclude subsequent U.S. investments. This restriction ensures that the investee has no prior exposure to U.S. VCs, so the initial U.S. entry represents the first potential channel through which knowledge can flow back to the United States via the VC channel, avoiding contamination from earlier U.S. VC contacts.

PitchBook also provides startup-oriented industry classifications and exit outcomes for

[5]Most analyses follow outcomes up to five years post-deal. Given right-truncation of the patent data at 2022, outcomes are measured only through 2022, limiting the sample to deals in 2017 or earlier.

[6]In recent years, several global arms of U.S. VC firms have been reorganized into independently operated entities (e.g., Sequoia Capital and GGV Capital in 2023). Because the sample ends in 2017, these changes do not affect the analysis.

portfolio companies. The industry codes are used as fixed effects in subsequent analyses, and exit status serves as a firm-level outcome to study the performance implications of cross-border knowledge spillovers. And detailed holdings data are also used to construct the network connections measure, which is described in section 2.6

Using data from PitchBook, Figure 2 illustrates the time trends in both the total number of U.S. VC deals and the share of those that are cross-border. The figure shows a clear upward trajectory in the volume of deals over time, alongside a notable increase in the share of deals involving foreign companies. Specifically, the share of cross-border deals has risen from around 10% in the early 2000s to over 30% in recent years. This trend is striking given the commonly held view that venture capital is a highly localized form of investment.

2.2 Patent Data

The patent data used in this study are sourced from PatentsView, which include detailed information on the universe of eventually granted patents in U.S. Patent and Trademark Office (USPTO) since 1975. I use application and grant dates, Cooperative Patent Classification (CPC) codes, assignee locations, inventors and detailed citation information from this dataset. Over the period between 1995-2022 [7], approximately 50% of patent assignees are U.S.-based entities, while the remaining 50% are foreign.

Although this paper examines knowledge spillovers at the global level, the exclusive use of USPTO data is justified for several reasons. First, the USPTO is one of the most prominent patent offices globally, and many foreign entities seek U.S. patents as a signal of high-quality innovation. Second, the primary focus of this study is on the patenting and citation behavior of U.S. entities, for which USPTO data are naturally the most comprehensive. Third, patent offices around the world differ significantly in terms of granting standards, classification systems, and legal frameworks, making cross-jurisdictional comparisons difficult without a common platform. Focusing on a single, widely recognized patent authority provides

[7]Following Lerner and Seru (2022), who note truncation issues in recent patent records, I restrict the sample to patents filed through 2022 to alleviate the truncation concern particularly in the citation measure.

consistency in measurement and enhances the comparability of results.

2.3 Sample Construction and Characteristics

I follow established procedures in the literature (NBER Patent Data Project; Bernstein (2015), Ma (2020), González-Uribe (2020)) to standardize company names in PitchBook and assignee names in PatentsView. I then merge the two datasets using a fuzzy match on company names combined with an exact match on headquarters city and country. Because the analysis focuses on firms whose innovation is observable in patent data, the final sample is limited to foreign deals in which the portfolio company filed at least one USPTO patent before receiving U.S. VC investment. This restriction ensures that patenting directions are measured prior to any potential influence from U.S. investors and, by design, focuses the analysis on firms with documented pre-investment knowledge creation—an essential precondition for studying subsequent diffusion. Consequently, the resulting sample is concentrated in more patent-active firms and industries, consistent with the focus of citation-based studies on observable knowledge flows. Estimates should be interpreted with this condition in mind.

The final sample of U.S. VC deals spans the period 2000–2017 and includes 776 foreign portfolio companies with 3,023 patents filed prior to the initial U.S. investment. These deals involve firms from 28 countries and cover 201 distinct four-digit CPC patent subclasses. The distributions of top 10 countries and top 10 patent classes represented in the sample are reported in Table 1 and Table 2, respectively. 84.66% of the deals originate from the top 10 countries, showing the concentration of cross-border investment activity. With the exception of mainland China, these top 10 countries are predominantly developed economies.

In Table 3, I report the composition of the sample by industry and deal stage over time. The industry distribution remains relatively stable across years, with activity concentrated in Healthcare and Information Technology. This concentration is consistent with the broader venture capital landscape, where innovation in these sectors attracts a disproportionately large share of VC investment (Lerner and Nanda, 2020). In the early 2000s, the sample was weighted more heavily toward early-stage cross-border VC investments relative to seed and later-stage deals. Over time, however, the composition across the three stages became more balanced, with the share of early-stage investments declining and the shares of seed and later-stage investments rising.

2.4 Patent Citations as a Measure of Knowledge Spillover

Patent citations have long been used as a proxy for knowledge spillovers, with one of the earliest and most influential introduction in Jaffe et al. (1993). All patent applications submitted to the U.S. Patent and Trademark Office (USPTO) are required to disclose relevant "prior art"—that is, previously granted patents or publications related to the new invention. As part of the patenting process, applicants are granted a temporary monopoly—typically lasting up to 20 years—in exchange for publicly disclosing detailed information about their inventions (Williams, 2017). This disclosure facilitates the dissemination of technological knowledge by allowing subsequent innovators to build upon prior art (Hegde et al., 2023), which is formally documented through citation linkages in patent records.

A common concern with using patent citations to measure knowledge spillover is that they may reflect heightened awareness or strategic behavior rather than genuine knowledge flow, since there is little direct cost to adding references. However, both over-citing and under-citing are constrained in practice. On one hand, adding extraneous citations creates legal risk for assignees. For example, in Blitzsafe Texas LLC v. Volkswagen Group of America, Inc., Blitzsafe alleged willful infringement of its audio integration patent. The Eastern District of Texas considered Volkswagen's citation of Blitzsafe's patent application during an inter partes reexamination as evidence of prior knowledge and therefore denied Volkswagen's motion to dismiss the pre-suit willful infringement claim. This demonstrates that excessive or strategic citing can be used against assignees in litigation, discouraging the inclusion of irrelevant prior art. On the other hand, omitting relevant citations is also difficult: applicants are legally required to disclose all known prior art, and professional patent examiners routinely supplement applications with missing references. These safeguards help ensure that patent citations reflect, to a meaningful extent, the actual technological influences underpinning new inventions. Taken together, the legal risks of over-citing and the regulatory requirements against under-citing make patent citations a credible and meaningful proxy for tracing knowledge flows.

2.5 Firm Outcomes

Firm-level outcomes provide complementary evidence of knowledge spillovers and allow assessment of their consequences for affected firms. To augment the citation-based measures, I construct firm-level indicators of innovative output: changes in the quantity and quality of patenting offer an outcome-based test of knowledge flow, since the most immediate manifestation of spillovers is a shift in innovation activity. I also track inventor participation (number of unique inventors) and firm success to evaluate whether spillovers expand a firm's innovation pool and translate into improved performance.

2.5.1 Firm Innovation Outcomes

I measure firm-level innovation productivity as the annual number of USPTO patents filed by U.S. companies that are eventually granted, assigning each patent to its application year. Because patent quality varies substantially across technologies and over time, raw counts can be misleading. I therefore also construct a measure of high-quality patent production, so the later analysis capture both the quantity and the quality of innovation.

Patent quality is assessed using two distinct indicators. The first is the number of forward citations a patent receives within five years of its application—a widely accepted proxy for patent quality in the literature. The second measure, drawn from Kelly et al. (2021), employs advanced textual analysis of patent documents to construct a "five-year importance" score. This score captures the extent to which a patent is both novel and influential, by comparing its textual similarity to prior and subsequent patents. Specifically, the importance score is defined as the ratio of forward similarity to backward similarity: forward similarity reflects how much future patents resemble the focal patent, while backward similarity indicates how much it resembles earlier inventions. A higher ratio—implying high forward and low backward similarity—signals that a patent is both original and impactful.

Because patent quality varies systematically across technologies and over time, raw quality levels are not directly comparable. I therefore construct within–CPC-subclass × application-year benchmarks and evaluate each patent relative to the mean quality of all patents filed in the same subclass and year. Instead of counting raw patent totals, the quality-weighted measure counts only those patents whose quality exceeds their subclass–year mean. Formally, for firm i in year t, the high-quality patent count is defined as follows:

$$Q_i = \mathbf{1}\{Quality_i > \overline{Quality_{c(t)}}\}$$

Let i denote a patent, and let $c(t)$ denote the three-digit CPC class of patent i, with application year t. For each patent, I construct two binary quality indicators based on alternative quality definitions. Specifically, set $Q_i = 1$ if patent i's quality measure exceeds the mean quality of all patents applied in the same year t within class c, and $Q_i = 0$ otherwise.

The high-quality patent output of firm j in calendar year t is defined as follows, where $I_{j,t}$ denotes the set of patents i applied by firm j in year t.

$$HighQualPatentCount_{j,t} = \sum_{i \in I_{j,t}} Q_i$$

I also construct an annual measure of inventor participation—the number of unique inventors named on each firm's USPTO patents in year t. This input-side metric captures the scale of the inventive workforce and clarifies which firm-side changes accompany increases in innovation output. By tracing this measure over time, I can distinguish mechanisms: growth driven by expansion of the inventor pool (extensive margin) versus gains driven by higher productivity among existing inventors (intensive margin).

2.5.2 Firm Success

To assess how spillovers translate into firm performance, I focus on a standard, observable outcome: successful exit. Comprehensive time-series financial data for startups are scarce, and interim private valuations are illiquid and largely expectation-driven. Accordingly, the literature commonly measures performance by eventual exit via IPO or M&A. I adopt this convention and define success using PitchBook's `LastFinancingDealType` and its date: a firm is classified as successful if its last deal type is "Merger/Acquisition" or "IPO." In my sample, the unconditional success rate is 26%.

2.6 Entity Connections to VC through Past Investment Networks

Differential exposure to the knowledge source can produce heterogeneous spillovers. This paper's central mechanism is diffusion through VC syndication networks. Accordingly, I measure exposure by the degree of connectedness between U.S. entities and the investing U.S. VC, constructed from historical co-investment (syndication) links under the premise that knowledge travels along investor networks to their portfolio companies. For relevance and to limit stale ties, eligible connections are restricted to those formed within the ten years preceding each VC investment in the sample.

Because VC networks evolve over time as new firms receive investments and join the network while older ties expire (connections more than 10 years old), I construct network connections at the VC investor–deal year level. The deal year corresponds to all years in which the investor makes a sample deal. For each investor–deal year, I classify U.S. firms into four mutually exclusive tiers based on their proximity to the investing VC. First-degree connections are U.S. firms that have previously received direct investment from the same VC—that is, current or past portfolio companies of the investing VC. Second-degree connections are portfolio companies of the VC's past co-investors, which I refer to as the close connections. Third-degree connections are portfolio companies of the co-investors' co-investors, which I refer to as the farther connections. Fourth-degree connections comprise all remaining U.S. firms not linked to the investing VC through the first three tiers; these are the most distant ties. Patents filed by these U.S. firms inherit their assignee's connection degree. Figure 1 provides a graphical illustration of this classification.

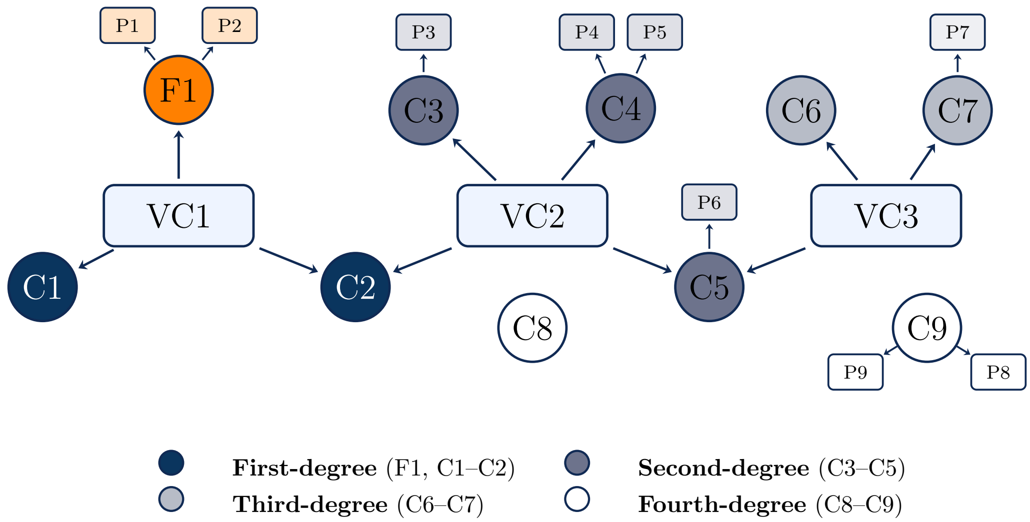


Figure 1: VC1's network and associated patents

Later analysis focuses on investment networks formed prior to the sample deal year. This restriction is necessary because, following an investment, firms that are more technologically similar to the foreign portfolio company may be more likely to form connections with the investing VC, raising concerns about endogeneity. A more detailed discussion on its application in empirical analysis is provided in later Section 3.2.1. The distribution of investor–year network connections to U.S. startup firms is reported in Table 4. On average, an investor has 7 first-degree connections, compared to 824 second-degree connections and 1900 third-degree connections. The relatively small number of first-degree connections highlights the contrast with the much larger networks that VCs maintain through indirect, past investment relationships. The larger pool of indirect connections, at both close and more distant levels, represents a potentially powerful channel for knowledge spillovers.

3 Citation Evidence of Knowledge Spillover

In this section, I document cross-border knowledge spillovers using U.S. citations to foreign patents. I first analyze aggregate effects, asking whether the investee's initial U.S. VC deal increases U.S. citation incidence to the investee's pre-existing patents. I then turn to mechanism and show that these spillovers travel primarily along VC syndication networks—rather than simple geographic proximity—underscoring the central role of prior co-investment ties in transmitting startup knowledge back to the United States.

3.1 Aggregate Response

I begin by examining aggregate "reverse" spillovers from U.S. VC investments in foreign startups. Specifically, I evaluate how the probability and frequency of U.S. citations to the investee's pre-existing patents change following the first U.S. VC investment. An increase in U.S. citations is interpreted as greater adoption of the foreign startup's technology within the U.S. innovation ecosystem.

I implement a difference-in-differences design with staggered treatment timing. I treat a foreign startup's initial U.S. VC investment as a quasi-exogenous shock to U.S. citations of its pre-investment patents and conduct the analysis at the foreign patent level.[8] To minimize prior U.S. influence on innovation, I retain only each foreign startup's first U.S. VC deal as the treatment. In this aggregate analysis, I further restrict the sample to patents filed no later than four years before the deal, which yields a balanced panel of citation outcomes from three years before to five years after the investment.[9] For each treated patent, I construct a set of never-treated control patents—excluding all patents produced by the foreign investee companies in the sample, both before and after the VC investment—matched exactly on country, CPC subclass (4-digit), application year, and grant year within a one-year window[10],

[8]Approximately 99% of treated patents are assigned to a single firm. In the rare cases where multiple sample firms jointly filed a patent, I randomly assign the patent to one of the collaborating firms.

[9]This reduced sample in aggregate analysis comprises of 302 U.S. VC deals and 1,118 treated patents.

[10]Results remain robust to enforcing the same grant year or using alternative maximum grant-year dif-

following Jaffe et al. (1993), who show that patents matched on these characteristics are similar in technological content.

The difference-in-differences (DID) specification is as follows:

$$USCitation_{i,p,t} = \alpha \ + \ \beta \left(\text{Post}_{p,t} \times \text{Treat}_i\right) \ + \ \gamma_i \ + \ \phi_{p,t} \ + \ \varepsilon_{i,p,t} \tag{1}$$

The outcome is measured in two ways. First, a binary indicator equals 1 if patent i receives any citation from U.S. entities in year t. Second, a frequency measure equals the natural log of the 1+ total number of U.S. citations received by patent i in year t. The DID estimates for these outcomes measure, respectively, the effect of VC treatment on the likelihood of receiving a U.S. citation and on the level of U.S. citations. Let p denote the matched set consisting of a treated patent and its matched controls. The treatment indicator $Post_{p,t}$ takes the value 1 in the year of the initial U.S. VC investment in the company owning patent i and remains 1 thereafter. Patent fixed effects (γ_i) absorb all time-invariant patent characteristics, so identification exploits within-patent changes over time. Matched-pair-by-year fixed effects are included to restrict comparisons to within matched sets and to allow for pair-specific trends in U.S. citation incidence. Standard errors are two-way clustered at the matched-pair and patent levels.

The results of the staggered DID analysis are presented in columns (1) and (2) of Table 5. Following treatment, the probability of any U.S. citation increases by 0.035 (18.4% of the treated group's pre-treatment mean), and the citation level rises by 4.4 percentage points in (1 + citations), which corresponds to an 11.2% increase relative to the treated group's pre-treatment mean of 0.69. [11]

I then estimate a dynamic version of the DID model by replacing $Post_{k,t}$ in Equation (1) with a series of event-time indicators that capture the number of years relative to the

ferences

[11] The DID coefficient from OLS on $\log(1+y)$ is $\hat{\beta} = 0.0432$. The percent change in $(1+y)$ is $100(\mathrm{e}^{\hat{\beta}} - 1) = 100(\mathrm{e}^{0.0432} - 1) = \mathbf{4.41}\%$. The fully DID-consistent level change is $\Delta y = (\mathrm{e}^{\hat{\beta}} - 1)\, r_C\, (1 + \bar{y}_{T,\text{pre}})$ with $r_C = (1 + \bar{y}_{C,\text{post}})/(1 + \bar{y}_{C,\text{pre}})$. Using $\bar{y}_{C,\text{pre}} = 0.356$, $\bar{y}_{C,\text{post}} = 0.407$, and $\bar{y}_{T,\text{pre}} = 0.692$ gives $r_C = 1.0376$ and $\Delta y = 0.0775$. As a share of the treated pre-mean: $\Delta y/\bar{y}_{T,\text{pre}} = 0.0775/0.692 = \mathbf{11.2}\%$.

investment. This specification allows tracing the evolution of U.S. citation to foreign patents over time and to formally test the parallel trends assumption. The expression is as follows:

$$USCitation_{i,p,t} = \alpha + \sum_{\tau=-3}^{5} \beta_\tau \cdot \mathbf{1}\{\text{EventTime}_{p,t} = \tau\} \times Treat_i + \ \gamma_i \ + \ \phi_{p,t} \ + \ \varepsilon_{i,p,t} \qquad (2)$$

Panels A and C in Figures 3 present event-study dynamics for U.S. citation likelihood and ln(1+NumCitations) around the initial U.S. VC investment in the foreign firm. The estimates show no differential pre-trends, supporting the identification strategy. Both outcomes begin to rise in the first year after investment—consistent with diffusion lags and the time required for U.S. entities to generate new patents that can cite the foreign invention—and remain elevated over the subsequent five years, with a gradual attenuation toward year five.

The preceding analysis, by itself, cannot establish a causal effect of VC investment on knowledge spillovers because two confounding factors may remain. First, selection on patent quality: even with patent fixed effects and matching on observables, treatment may correlate with time-varying unobservables that make certain patents intrinsically more citeable. In the absence of investment, such patents would attract more U.S. citations over time, biasing estimates upward. Second, anticipatory investment: U.S. VCs may select foreign startups whose technologies align with emerging U.S. needs. In that case, treated patents would receive more U.S. citations even without any spillover, simply because they sit in rising technological fields. While the event-study shows parallel pre-trends alleviate concerns about diverging trajectories before investment, I implement direct tests targeted at these alternatives in the sections that follow.

I first address the selection on unobserved quality concern. I implement a placebo test that replaces the outcome with citations from "third countries"—all countries other than the United States and the investee's home country. Because the investment links U.S. VCs to a startup in the investee country, there is no direct channel through which third-country entities should change their citation behavior. At the same time, third-country citation trends should reflect shifts in the perceived technological quality of the patents, including components unobservable to the researcher. Accordingly, if third-country citations to treated patents do not rise relative to matched controls around the investment—while U.S. citations do—the main DID effect is unlikely to be driven by selection on time-varying patent quality. This placebo directly targets the first concern; the second concern on U.S. trend anticipation is examined in Section 3.2.

In the placebo test, I re-estimate equations (1) and (2) after replacing the outcome with citations from third countries. Specifically, I use two measures analogous to the U.S. case: $\mathbf{1}\{\text{Any 3rd country citations}\}_{i,p,t}$ and $ln(1 + \#\text{ of 3rd-country cites})_{i,p,t}$. The results are reported in columns (3) and (4) of Table 5, and the dynamics of the study appears in panels B and D of Figure 3. The DID estimates are statistically indistinguishable from zero and economically small. In the dynamic specification, there is no post-investment pattern resembling the main results and no meaningful divergence between treated and control patents until year five.

To synthesize the main and placebo evidence, I estimate a triple-differences (DDD) specification that directly contrasts the DID for U.S. citations with the DID for third-country citations. This approach yields a single, U.S.-specific spillover coefficient that (i) sharpens inference by pooling information across both outcome families, (ii) nets out common shocks to patent quality/exposure that affect all foreign citations, and (iii) isolates the incremental shift attributable to the VC-mediated U.S. channel. In short, the DDD provides a tighter, more interpretable summary of the cross-border spillover effect than reading the two DIDs separately. The specification is as follows:

$$Citation_{i,p,t,m} = \alpha \ + \ \beta \left(\text{Post}_{p,t} \times \text{Treat}_i \times \text{Main}_m\right) \ + \ \gamma_i^{(m)} \ + \ \phi_{p,t}^{(m)} \ + \ \varepsilon_{i,p,t,m} \qquad (3)$$

I estimate the DDD on a stacked panel that pools the main (U.S.-citation) and placebo (third-country citation) samples, with $m \in \{\text{Main}, \text{Placebo}\}$ indexing the sample. The fixed effects $\gamma_i^{(m)}$ and $\phi_{p,t}^{(m)}$ are interacted with m, allowing patent-specific baselines and matched-pair-by-year trends to differ across samples. The coefficient β is the triple difference, i.e., $DDD = DID^{US} - DID^{3rd}$. Results (reported in columns (5) and (6) of Table 5) show a positive, statistically significant β of similar magnitude to the main U.S. DID, indicating that the post-investment increase in citations is specific to U.S. citers rather than shared with third-country citers. This pattern strengthens the view that U.S. VCs transmit knowledge back into the U.S. innovation ecosystem and further mitigates concerns about selection on patent quality. It also suggests that VCs do not foster knowledge flows simply by picking the highest-quality patents within technology $\times$ year cells. A more plausible mechanism is early discovery of foreign startup technologies and the implementation know-how VCs accumulate, which facilitates adoption and better application by U.S. entities.

3.2 VC Network Connections and Knowledge Spillover

To further investigate VC's role behind the aggregate knowledge flows, I test whether spillovers vary with the strength of past syndication links between U.S. entities and the investing VC. This analysis targets the central channel—knowledge diffusion through VC networks—using patent citations as the observable record. I then benchmark the network effect against two alternatives: geographic proximity to the investing VC and a domestic setting where other diffusion channels, such as social connections and labor mobility, are stronger. Taken together, these tests assess whether VC syndication networks are the primary conduit for cross-border knowledge flows.

I measure each U.S. entity's connection to the investing VC by its proximity in the VC's historical syndication network (details in Section 2.6). I exclude first-degree connections because they share the same VC investor as the foreign investee, raising reverse-causality and selection concerns (e.g., the VC may target foreign deals that complement its existing U.S. portfolio). The analysis therefore focuses on second- and higher-degree connections—firms outside the investing VC's direct portfolio, over which the VC has no control and in which it holds no financial stake or claim to benefits. By construction, this design mitigates endogeneity and isolates VC-mediated knowledge diffusion beyond the VC's own portfolio, extending evidence on within-portfolio flows (González-Uribe, 2020).

I measure geographic proximity with an indicator equal to 1 if the citing U.S. patent assignee is located in the *same city* as the U.S. VC that made the cross-border investment. Because geographic proximity is a well-documented channel for knowledge diffusion, entities near the investing VC—the likely carrier of knowledge from the foreign startup—may be more exposed to spillovers. This test assesses whether location remains an important determinant of cross-border startup knowledge flows and, by juxtaposing it with the network-based results, clarifies the relative importance of geographic proximity versus syndication networks in transmitting knowledge.

3.2.1 VC Investment Syndication Networks Channel

To study how syndication-network proximity shapes knowledge-flow intensity, I shift the unit of observation from the foreign investee's patents used in the aggregate analysis to U.S. citing patents. This recasting lets me directly observe the citation behavior at patent level. For each U.S. patent, I assign its connection tier to the investing VC based on pre-investment syndication ties, as defined in Section 2.6; when a patent has multiple assignees, it inherits the closest tier (minimum network distance) across owners. I then test whether, following a U.S. VC cross-border investment, more closely connected U.S. patents are more likely to cite the treated foreign patent.

Directly comparing citations to the treated patent across network tiers would conflate network proximity with differences in industry and location composition, which affect technological relevance and baseline citation propensities. To ensure comparability, I define for each treated patent a citation risk set of U.S. patents whose assignees have revealed demand for closely related technologies—operationalized as U.S. patents that cite other patents *sim-*

ilar to the treated foreign patent. Similarity is defined by matching on country, 4-digit CPC subclass, and application year. The outcome is the probability that a U.S. patent cites the treated foreign patent *conditional on* making a citation within this technology–time cell.[12]

I restrict the analysis to network ties formed before the U.S. VC's investment in the foreign company to rule out post-investment, endogenous link formation. The concern is the following: after a cross-border deal, other VCs that previously syndicated with the investing VC may learn about the foreign technology and then begin backing U.S. startups in adjacent or related technological areas—precisely the firms most likely to need or adopt that technology. Therefore introducing reverse causality: network proximity would appear to raise citation likelihood, when in part the network proximity is a result of higher citation likelihood formed post sample cross-border investment.

I analyze the full sample of 776 cross-border VC deals, covering 3,023 foreign patents filed before the initial U.S. VC investment, and estimate citation likelihoods in an event window from three years before to five years after the deal year. [13] Because the design conditions on citations to similar patents, a treated patent enters the estimation only if it—or at least one of its similar patents—receives at least one U.S. citation during the sample period. The specification is as the following:

$$1\{\text{j cite treated}\}^k_{ij,t} = \alpha + \beta\, i.NetworkTier^k_j + \gamma\, Post^k_t \times i.NetworkTier^k_j + \text{FE} + \epsilon^k_{ijt} \quad (4)$$

I estimate the model using both a linear probability model and a logit specification. The unit of observation is U.S. citing patent $\times$ foreign patent $\times$ year. Let i index a foreign patent, k the group of foreign patents similar to the treated patent (including the treated patent itself), j a U.S. citing patent, and t the calendar year. The outcome $1\{\text{j cite treated}\}^k_{ij,t}$

[12] Results are robust to alternative similarity definitions: adding a similar grant-year restriction, or relaxing the application-year match to a $\pm x$-year window for reasonable x. Robustness test on one alternative similarity definition is described in Section 5

[13] Results are robust to imposing the same restriction as in the aggregate analysis—keeping only foreign patents filed more than three years before the initial U.S. VC deal—so that every treated patent is observed throughout the entire $[-3, +5]$ window.

equals 1 if j cites the treated patent within group k (as opposed to other similar patents), and 0 otherwise. The variable $NetworkTier_j^k \in 2, 3, 4$ indicates the citing patent's network proximity to the U.S. VC that invested in the foreign assignee of the treated patent in group k (second-, third-, or fourth-degree connection). First-degree connections—defined as the VC's own direct portfolio companies—are excluded because the VC's investment choices are likely correlated with those firms' technological trajectories, raising endogeneity concerns.

I include granular fixed effects to absorb common citation trends among observably similar U.S. citing patent j. First, I add group-by-year-by-citing-city fixed effects, $k \times t \times$ City (FE1), which restrict comparisons to citers in the same city and year within group k but with different VC-network proximity. This design isolates exposure to the investing VC from within-city peer effects and local shocks—important given documented geographic clustering in innovation and diffusion (reflection concerns). I then further tighten controls to $k \times t \times$ City $\times$ Citing Subclass, ensuring comparisons occur within the same technology class as well as city and year. Together, these fixed effects absorb highly granular variation in baseline propensities to cite the treated foreign patent; combined with conditioning on citations to *similar* patents within group k, they sharpen identification of the effect of VC network proximity on observed knowledge flows. Standard errors are clustered at the k level.

Results are reported in Table 6. Estimates are expressed relative to the baseline—U.S. patents associated with firms that are fourth-degree connections to the investing VC. In the pre-investment period, conditional citation likelihoods do not differ significantly across network tiers. After the U.S. VC investment, however, firms with closer ties to the investing VC exhibit higher citation probabilities, with increases of 2.55–3.78 percentage points; these effects are economically meaningful relative to the pre-treatment mean of 2.83 percentage points. By contrast, post-investment citation rates for third- and fourth-degree connections are statistically indistinguishable. Taken together, the evidence indicates that U.S. firms with tighter network proximity to the investing VC experience stronger cross-border knowledge spillovers, consistent with VC syndication networks facilitating the transmission of knowledge from foreign investees back to the United States.

This finding also addresses the second concern raised in Section 3.1, namely that U.S. VCs may select foreign startups whose technologies align with future U.S. demand. Such alignment could arise because VCs intentionally target technologies expected to expand domestically or because their preferences inadvertently track the U.S. innovation trajectory. If rising domestic needs were the sole driver, then conditioning on granular trends via patent subclass × city × time fixed effects should leave little residual variation. Instead, I document a pronounced post-investment increase in citations among U.S. patents most closely connected to the investing VC. The concentration of effects among network-proximate firms points to a VC-network transmission channel for cross-border knowledge spillovers, rather than predictive alignment with U.S. technology demand.

3.2.2 Location Proximity Channel

To benchmark the syndication-network results against a canonical alternative channel, geographic proximity, I test whether spillovers vary with distance from the investing U.S. VC. Using the same framework as above, I examine whether firms located in the VC's city exhibit stronger post-investment citation responses than firms elsewhere. The specification is:

$$1\{\text{j cite treated}\}^k_{ij,t} = \alpha + \beta\, 1\{SameCity\}^k_j + \gamma\, Post^k_t \times 1\{SameCity\}^k_j + \text{FE} + \epsilon^k_{ijt} \tag{5}$$

$1\{SameCity\}^k_j$ measures geographic proximity between the citing U.S. patent and the investing VC in cohort k. It equals 1 if the citing patent j is filed in the same city as the U.S. VC investor in a cross-border deal, and 0 otherwise. I include fixed effects at the $k\times$ citing-patent-subclass × t level and at the k × citing-patent-subclass × VC-network tier × t level. The subclass dimension restricts comparisons to citing patents within the same CPC subclass, controlling for technological relevance to the investee's patents; interacting with the VC-network tier allows for differential trends across network proximity levels.

Results are reported in Table 7. Across specifications, the coefficient γ, which captures the differential change in the likelihood of citing the treated patent (conditional on relevant characteristics), is statistically indistinguishable from zero. These findings indicate that locating in a same city as the investing U.S. VC does not significantly increase the likelihood of citation. Unlike the strong spillover patterns observed among firms with close network ties to the investing VC, spatial proximity does not appear to facilitate additional knowledge transfer. This contrast underscores the importance of investment network channels, rather than geographic closeness, in mediating the VC-driven cross-border knowledge spillovers.

3.2.3 Domestic Case Comparison

This paper focuses on how VC investment networks foster knowledge spillovers, a feature that is not unique to cross-border investments. However, the importance of this network-driven mechanism may be amplified in the international context due to the greater frictions that impede cross-border knowledge flows, particularly for knowledge originating from startups. Many conventional channels of knowledge spillovers operate less effectively across national boundaries. These channels include the migration of inventors across locations, the maintenance of social and professional relationships among inventors, and the interlinked supply chains of operating firms.

In this section, I compare the role of VC networks in transmitting knowledge across borders with their role in a purely domestic setting. I replicate the analysis from Section 3.2.1 and Section 3.2.2, but replace cross-border deals with initial investments by East Coast VCs into West Coast companies. This pairing preserves substantial geographic distance—maintaining frictions comparable to the cross-border case—while remaining within the U.S., where both regions host dense VC and startup activity. Then, I ask whether East Coast firms that are more closely connected to the investing VC through prior syndication networks are more likely to cite the West Coast investee's patents after controlling for relevant characteristics.[14] The empirical specifications mirror Equations (4) and (5), testing both the VC-network and geographic-proximity channels.

Results are reported in Table 8 and Table 9. As in the cross-border case, estimates are benchmarked to entities with low VC-network connectivity (fourth-degree connections). Domestically, stronger network ties are not associated with a statistically significant post-investment increase in the likelihood of citing the investee's patents, and co-location in the same city as the investing VC likewise shows no differential effect. These null results do not imply that VC networks are irrelevant within the U.S.; rather, abundant alternative diffusion channels (e.g., geographic proximity, labor mobility, and social ties) likely attenuate the marginal role of syndication links—especially if learning occurs before any network-mediated transmission. The contrast with the cross-border findings underscores that VC networks are particularly important when other channels are constrained.

4 Firm-Level Evidence of Knowledge Spillovers and Performance Effects

The citation-based analyses above document cross-border knowledge flows from foreign investees to the United States, concentrated among U.S. firms with closest syndication ties (the 2nd degree connections) to the investing VC. I next provide firm-level evidence by examining changes in the quantity and quality of patenting—both overall and within technology fields directly related to the foreign investees. If VC networks transmit knowledge from these investees, closely connected U.S. firms should expand innovative output, with disproportionately larger gains in investee-related technologies.

In addition, I assess impacts on closely connected U.S. firms along two margins: (i) inventor participation—the annual number of unique inventors listed on the firm's patents[15]—and

[14] The definition of network connections is the same as in Section 3.2.1. Connections are based on past syndication between the investing East Coast VC and any U.S. VC (not limited to East Coast VCs).

[15] In the absence of comprehensive firm-level employment data—especially for startups—I observe con-

(ii) subsequent success, proxied by exit via IPO or M&A. Cross-border knowledge spillovers can affect both outcomes: greater exposure through VC investor connections should raise innovative output and prompt firms to broaden their inventor base, and stronger innovation is associated with a higher likelihood of successful exit.

4.1 Total Patent Production and Quality

I first assess whether knowledge spillovers manifest as increases in firms' innovation productivity. The unit of observation is the U.S. company × year. Outcomes are the number of patents and the number of high-quality patents produced by U.S. companies, as defined in Section 2.5.1. The sample is restricted to U.S. firms that filed at least one USPTO patent by 2022 so that patent-based measures meaningfully capture innovation activity, excluding non-patenting firms whose innovations are not observable in patent data.

I employ a difference-in-differences design with staggered treatment timing and compare second- with third-degree connections: second-degree firms are treated, and third-degree firms serve as controls. As shown in Table 6, evidence of citation-based spillovers is concentrated among second-degree connections, whereas effects for the third and fourth degrees are weak and statistically indistinguishable. Because third-degree firms are the nearest network neighbors yet show no detectable effects and resemble the fourth degree (the most distant tier) they provide an appropriate counterfactual. Staggered treatments are defined at the investor × deal-year level of sample cross-border VC deals described in Section 2.3. The analysis covers the window from −3 to +5 years around each cross-border deal. To maintain a balanced panel, network ties must be in place at least three years before the deal year. I further restrict to companies that remain active through the relevant evaluation window to avoid mechanical effects of failure on measured innovation outputs.

The identification strategy relies on two key assumptions: (1) that assignment to the

tributing inventors only. Participation does not necessarily imply employment; inventors may contribute via outsourcing or part-time collaborations. I therefore interpret changes in inventor counts as shifts in the firm's innovation resource pool or input, not in headcount.

second- or third-degree connection group is orthogonal to the foreign investment decision of the U.S. VC, and (2) that in the absence of treatment, these two groups would exhibit parallel trends in outcomes. The first condition is satisfied by construction: under the network definition, VCs do not hold financial interests in, or exert operational influence over, their second- or third-degree connections. Thus, investment decisions are unlikely to be influenced by these firms. Additionally, by restricting to connections formed at least three years prior to the foreign investment, I further mitigate concerns about reverse causality or endogenous link formation. To support the parallel trends assumption, I include granular fixed effects and control variables to account for potential differences in trends between firms with second- and third-degree connections to the investing VC in characteristics such as industry, geographic location, and historical patenting activity. The specification is:

$$y_{i,k,t} = \alpha + \beta\, Post_{k,t} \times \mathbf{1}\{\text{Is 2nd Degree Connected}\}_{i,k} + Control_{i,k,t} + \gamma_{k,\chi,t} + \phi_i + \epsilon_{i,k,t} \quad (6)$$

The regression is estimated using Pseudo-Poisson Maximum Likelihood (PPML). Let i index U.S. companies and t denote calendar years. The cohort k is defined at the investor–year level and includes all U.S. companies that are second- or third-degree connections to k, based on VC network connections formed at least three years prior to the deal year of cohort k. [16]

The specification includes two sets of fixed effects: cohort $\times$ characteristics $\times$ year ($\gamma_{k,\chi,t}$) and firm (ϕ_i). Firm fixed effects absorb all time-invariant attributes of i. The characteristics vector χ comprises (i) industry and (ii) a pre-treatment patent category. Industry is defined using PitchBook's industry code system (160 categories in our sample). To control for heterogeneity in baseline patenting while preserving power, I sort firms into five pre-treatment patent categories based on patenting intensity in the three years preceding the relevant deal year: firms with zero patents are assigned to category 1; the remaining firms are split into four groups by quantiles of the nonzero pre-treatment patent count distribution. Results are

[16] In rare instances, a U.S. VC investor serves as the initial investor in multiple foreign companies within the same year. In such cases, these investments are combined and treated as a single cohort k.

robust to using all patents filed before the deal year instead of the three-year window. The cohort × industry × pre-treatment patent category × year fixed effects thus absorb within-cohort time trends tied to these characteristics and restrict identification to within-cohort comparisons of second- versus third-degree connections among observationally similar firms.

To account for potential clustering and correlated innovation activity at the city level, I include a control variable $Control_{i,k,t}$, defined as the outcome produced by all VC-backed firms located in the same city as firm i, excluding firm i's own outcome (i.e., a leave-one-out measure). This controls for city-level shocks to innovation productivity that could potentially drive the firms innovation outcomes. I also use a stricter way to capture city-level innovation productivity trend by adding city*year fixed effect. The estimation results are presented in Panel A of Table 10, columns 1-2. Results show that cross-border VC investments lead to an 10.45% increase in overall patent production.[17]

Patent counts alone may not capture true innovative output because patent quality varies widely. I therefore re-estimate Equation (6) using two measures of high-quality patent production defined in Section 2.5.1[18] To accommodate differences in baseline innovation quality, I redefine pre-treatment patent categories using the three-year pre-investment average of high-quality output and discretize this measure into five bins, analogous to the main specification based on raw counts. Results appear in Panel A of Table 10, columns 3–6. Across both quality measures (citation-weighted and importance-weighted) and under both specifications that control for location-based productivity trends via controls and fixed effects, high-quality patent output increases by an average of 9.94%.

To further understand the changes in outcomes over time and test the parallel trend assumption, I replace the $Post_{k,t}$ with the time dummy indicating years to the event date. Specification is as the following:

[17] The percentage change in outcome is calculated as $e^{\beta} - 1 * 100$, where β is the estimates in equation (6)

[18] Both measures require five-year post-filing citation statistics. Because filings are observed up to five years after each deal year and the sample includes deals through 2017, I restrict the high-quality analyses to deals in 2012 or earlier to maintain a balanced five-year window, which reduces the sample relative to the full-sample specifications.

$$
\begin{aligned}
y_{i,k,t} = \alpha \ + \ \sum_{\tau=-3}^{5} \beta_\tau \, \mathbf{1}\{\text{EventTime}_{k,t} = \tau\} \times \mathbf{1}\{\text{Is 2nd Degree Connected}\}_{i,k} \\
+ \, Control_{i,k,t} \ + \ \gamma_{k,\chi,t} \ + \ \phi_i \ + \ \epsilon_{i,k,t}
\end{aligned}
\tag{7}
$$

Figure 4 reports event–study estimates for total patent output (Panel A) and high-quality output, measured as citation-weighted (Panel C) and importance-weighted (Panel D) counts, using the specification with city × year controls. Figure 6 in the Appendix presents the corresponding estimates from the specification with city × year fixed effects. Pre-treatment coefficients are near zero and jointly insignificant, indicating no differential trends between second- and third-degree firms before the cross-border deal. After the investment, outcomes for second-degree firms rise relative to controls and remain elevated over the five-year horizon. The lack of pre-trend differences, together with the post-investment divergence, supports the parallel-trends assumption and a causal interpretation: total and high-quality patent output increase significantly following U.S. VC investment, consistent with greater exposure to VC-mediated knowledge spillovers. These results underscore the role of VC networks in raising both the quantity and the quality of firm-level innovation.

4.2 Patent Productions in Investee-related Fields

I next test whether spillover effects are stronger in technologies most closely related to the foreign investees. For each cohort k, I define that cohort's "invested classes" as the 4-digit CPC subclasses in which the foreign investee filed patents before its initial U.S. VC investment. I then re-estimate Equations (6) and (7) after replacing each firm's outcome with the corresponding measure restricted to patents in the cohort's invested classes. Results are reported in Panel B of Table 10. The event study dynamics appear in Figure 5 (city × year controls) and Figure 7 (city × year fixed effects).

Effects are stronger within the invested classes than in the full technology set. Patent output in the invested classes rises by 22.26%, while high-quality output increases by 34.45% on average, averaging across the two quality measures and across specifications that account for location-specific productivity trends (city × year controls and city × year fixed effects). These results indicate that spillovers concentrate in technologies closest to the foreign knowledge source, the foreign investee, with especially large gains in patent quality.

4.3 Inventor Participation

To gain deeper insight into firm-level innovation dynamics, and asses the impact from the increase innovation productivity on firms, I examine how the number of unique inventors contributing to patenting activity evolves over time. Tracking changes in active inventors provides a measure of innovation input of firms and helps assess whether increases in innovation output are driven by higher individual productivity or by a growing pool of contributors. I apply the same empirical framework used in Sections 4.1 and 4.2, this time focusing on inventor activity. The outcome variables are (i) the number of unique inventors at firm i who produced at least one patent in year t, and (ii) the number of unique inventors at firm i producing patents specifically within the invested classes of cohort k in year t. Results on DID estimates are presented in columns 7 and 8 in Table 10. Dynamic responses are presented in Panel B of Figure 4, and Figure 5.

The results show that the number of unique contributing inventors involved in firms' patent production increases by 11.96% overall and by 21.29% in the invested classes. These percentage gains closely mirror the observed growth in patent output, suggesting that the increase in innovation activity is accompanied by broader inventor participation. In particular, as second-degree connected firms produce more patents following U.S. VC investment, a greater number of inventors are engaged in patenting efforts. While this does not necessarily imply an increase in inventor headcount in a firm, it suggests that, in response to knowledge spillovers, firms increase their innovation resource inputs.

4.4 Firm Success

This section evaluates whether the innovation gains documented above translate into improved firm performance. Because startups are not subject to standardized financial reporting and many early-stage firms have little or no revenue, private valuations are opaque and largely investor-driven until realized at exit. Consistent with common practice, I therefore measure performance using a binary indicator for a successful exit—an observable, widely accepted benchmark in the startup ecosystem. Using PitchBook, a firm is coded as successful if its `LastFinancingDealType` is recorded as "Merger/Acquisition" or "IPO." In the full PitchBook sample of VC-backed firms, the mean probability of achieving a successful exit by 2017 (the sample end date) is 26.99 percentage points.

To assess effects on firm success, I adopt the same comparative approach used for innovation analysis and contrast five-year exit outcomes for second- versus third-degree connected ever-patented U.S. startups to the investing VC following its cross-border deal in the treatment sample. Specifically, within each investor × deal-year cohort, I compute the difference in five-year success rates between second- and third-degree connected companies after the cohort VC's foreign investment.[19] I restrict the sample to companies that remain active through the deal year, as success cannot be defined for firms that failed beforehand. The estimating specification is:

$$\mathbf{1}\{\text{Success}\}_{i,k} = \alpha + \beta\,\mathbf{1}\{\text{Is 2nd Degree Connected}\}_{i,k} + \gamma_{k,\chi,t} + \phi_j + \epsilon_{i,k} \tag{8}$$

I estimate the specification using a linear probability model. Let i index U.S. companies that are second- or third-degree connections to cohort k, where a cohort is defined at the VC investor × deal-year level. The outcome $\mathbf{1}\{\text{Success}\}_{i,k}$ equals 1 if company i achieves a successful exit (as defined above) and 0 otherwise. The indicator $\mathbf{1}\{\text{Is 2nd Degree Connected}\}_{i,k}$ equals 1 for second-degree connections to cohort k and 0 for third-degree connections. I in-

[19] Results are qualitatively similar under alternative time windows; see X for estimates using different horizons.

clude investor fixed effects ϕ_j for each firm's most recent direct VC investor, since quality and style of direct investors may influence exit timing and likelihood. To compare observationally similar firms, I use $\gamma_{k,\chi,t}$—a set of fixed effects interacting cohort k with industry, first financing year, first financing type, and calendar year (cohort $\times$ industry $\times$ first financing year$\times$first financing type$\times t$)—so identification comes from within-cohort contrasts among firms sharing these exit-relevant attributes. I also estimate a richer specification that augments $\gamma_{k,\chi,t}$ with the firm's pre-treatment patenting category (as in Equation 6), i.e., cohort $\times$ industry $\times$ first financing year $\times$ first financing type $\times$ pre-treat patent category $\times\, t$. The first financing year and type proxy for VC stage, while the pre-treat patent category captures prior innovation intensity. Industry follows PitchBook's primary industry code. Standard errors are two-way clustered at the firm and cohort levels.

Because exits are one-time outcomes, they do not permit pre-trend tests. To ensure the results are not driven by intrinsic differences in exit propensity between second- and third-degree firms unrelated to cross-border VC investment, I conduct a placebo exercise. I assign a placebo deal year six years before the actual investment[20]. I then reconstruct second- and third-degree connections using ties to the investing VC formed in the ten years preceding the placebo year and re-estimate the baseline specification. This test asks whether, absent a real cross-border investment, second-degree firms exhibit higher exit rates than third-degree firms after conditioning on observables. Finding no such difference supports the view that the main effects reflect the actual VC investment rather than pre-existing trends or selection. A caveat is that network connections is dynamic: the sets of second- and third-degree firms linked to a given VC can change as new ties form and old ties lapse. Accordingly, the identifying assumption is that the baseline gap in exit likelihood between second- and third-degree connections does not vary materially over time.

Results from the main firm–success analysis are reported in columns (1) and (2) of Table 11, while the placebo estimates are shown in columns (3) and (4). The main specification

[20]The six-year offset provides a five-year post window while avoiding overlap with the real treatment period.

indicates that the five-year likelihood of a successful exit is 1.3 percentage points higher for second-degree connected firms relative to third-degree connected firms, corresponding to 5.18% of the sample mean. By contrast, the placebo estimates are small and statistically insignificant, consistent with the view that there are no inherent differences in exit likelihood between second- and third-degree connections to the same investing VC.

I next examine heterogeneity in exit effects along two dimensions—sector relevance and network strength—within second-degree connections. Evidence that performance gains are larger when the U.S. startup operates in the investee's sector or when the connecting ties are stronger would further support a VC-network channel for firm-level impacts.

To test sector relevance, I interact the second-degree indicator with a same-sector dummy equal to one if U.S. startup i and the cohort k foreign investee share the same PitchBook top-level sector. Because sector needs are broad and many technologies apply across industries, I use PitchBook's six top-level sectors (IT, Healthcare, B2B, B2C, Energy and Materials, and Financials). These broad categories accommodate cross-industry applicability but are not fully precise; for example, large-scale data-processing tools may be valuable in both IT and Healthcare. Accordingly, a VC knowledge spillover channel predicts a larger effect within the same sector, while allowing for nonzero effects across different sectors. The specification is:

$$\begin{aligned}\mathbf{1}\{\text{Success}\}_{i,k} = \alpha + \beta_1\,\mathbf{1}\{\text{Is 2nd Degree Connected}\}_{i,k} \times \mathbf{1}\{\text{Same Sector}\}_{i,k} \\ + \beta_2\,\mathbf{1}\{\text{Same Sector}\}_{i,k} + \gamma_{k,\chi,t} + \phi_j + \varepsilon_{i,k}.\end{aligned} \tag{9}$$

To test variation by network strength, I partition second-degree connections into "higher" and "lower" quality. For each cohort k—defined by the cross-border investing VC (the target VC) and the deal year—I count syndications over the prior ten years between the target VC and its past syndication partners. For each second-degree firm i, I sum the target VC's historical syndications with i's direct investors, rank firms within cohort, and classify those above the median as higher-quality ties and those below as lower-quality ties. I then treat network status as three categories—second-degree (high), second-degree (low), and third-degree—and estimate:

$$\mathbf{1}\{\text{Success}\}_{i,k} = \alpha + \beta \times \{\text{Connection Strength}\}_{i,k} + \gamma_{k,\chi,t} + \phi_j + \epsilon_{i,k} \tag{10}$$

$\{\text{Connection Strength}\}_{i,k}$ denotes the three categories defined above. Larger coefficients for higher-quality second-degree ties relative to lower-quality ties provide evidence that stronger VC-network links amplify performance effects.

Table 12 reports heterogeneity in exit effects. Columns (1)–(2) show that second-degree firms in the same sector as the foreign investee have an additional 0.70–0.87 percentage-point higher five-year exit probability (interaction term), while third-degree firms exhibit no sector differential (the estimate β_2 on $\mathbf{1}\{\text{Same Sector}\}$ is insignificant). Columns (3)–(4) indicate that higher-quality second-degree ties are associated with a 1.62–1.65 percentage-point increase in exit likelihood relative to third-degree firms; lower-quality second-degree ties show a 0.90–1.15 percentage-point increase—about 40% smaller. Together, these patterns are consistent with a network-mediated channel: spillover benefits are stronger when sector relevance is higher and when the VC syndication link is stronger.

5 Robustness

In Section 3.2, I assess the role of past VC syndication networks by estimating, conditional on a U.S. patent citing a foreign patent similar to the treated one, the probability that it cites the treated patent itself. There, "similar" is defined at the country $\times$ CPC subclass $\times$ application-year level. As a robustness check, I tighten this risk set to account for grant-lag differences that may correlate with patent characteristics. I redefine "similar" to require the same country, CPC subclass, and application year, and a grant year within ± 1 years. I then re-estimate Equations 4 and 5 to test the effects of VC network channel and geographic proximity channel, using this revised universe of similar patents. Results, reported in Table 13 and Table 14, are qualitatively unchanged, indicating that the main findings are robust to a stricter similarity definition and are not sensitive to the construction of the risk set.

Building on the network analysis, I complement the average post-versus-pre effect with an event study of the conditional citation likelihood. The event study traces the raw likelihood to cite of different network strength over time around the cross-border investment and provides a visual check for pretrends in change of such likelihood. The estimating sample is not a balanced panel because each foreign patent appears only in years when it receives at least one U.S. citation; as a result, composition can vary across event times, but the coefficient path remains informative about timing and persistence. I estimate a version of Equation 4 that replaces $\text{post}_{k,t}$ with event-time indicators $\mathbf{1}\{\text{EventTime}_{k,t} = \tau\}$ for $\tau = -3, \ldots, 5$. The specification is as follows:

$$\begin{aligned} 1\{\text{j cite treated}\}_{ij,t}^{k} &= \alpha + \beta\, i.NetworkTier_j^k \\ &\quad + \sum_{\tau=-3}^{5} \gamma_\tau\, \mathbf{1}\{\text{EventTime}_{k,t} = \tau\}_t \times i.NetworkTier_j^k + \text{FE} + \varepsilon_{ijt}^{k}. \end{aligned} \tag{11}$$

I estimate the specification separately by network degree (second, third, and fourth). The fixed effects mirror those in Equation 4, except they are not interacted with time, since the event-time indicators require time variation for identification. Event-study coefficients are reported in Figure 8. For second-degree connections, the conditional likelihood of citing the treated patent rises only after the foreign VC investment—showing a statistically significant post-treatment increase with no evident pretrend. By contrast, third- and fourth-degree groups exhibit much smaller, statistically insignificant changes. These dynamics reinforce that VC-induced cross-border knowledge spillovers accrue primarily to close network ties.

In the firm-level innovation analysis, I estimate percentage changes in output using pseudo- Poisson maximum likelihood (PPML). As a robustness check, and to understand effects at the extensive margin, I re-estimate the designs from Sections 4.1 and 4.2, replacing the outcomes with the binary indicators $\mathbf{1}\{\text{Produce Patent}\}_{i,k,t}$ and $\mathbf{1}\{\text{Produce High-Quality Patent}\}_{i,k,t}$. I estimate these specifications by OLS (linear probability models). This exercise both isolates extensive-margin responses and demonstrates robustness to an alternative estimator. Results reported in Table 15 show statistically significant increases in the likelihood of patenting and of producing at least one high-quality patent: total patenting likelihood rises by 1.7 percentage points (4.5% of the treated pre-mean), and total high-quality patenting likelihood rises by 1.1 percentage points (3.4% of the pre-mean). Within foreign investee–related classes, patenting likelihood increases by 0.53 percentage points (11.3% of the pre-treatment mean), and high-quality patenting likelihood increases by 0.24 percentage points (9.5% of the pre-treatment mean). These consistent extensive-margin effects, confirmed with an alternative estimator, reinforce that knowledge flows to close VC syndication networks.

6 Conclusion

U.S. venture capital has become increasingly international. Because VCs are deeply involved with portfolio companies and rely on syndication networks, they are well positioned to transmit starup ideas across borders. I show that U.S. VC investments abroad cause knowledge flow back to the United States: after an investee's first U.S. VC deal, the probability that its pre-existing patents receive a U.S. citation rises by 18%.

Patent-level tests indicate that spillovers travel along prior syndication ties rather than geographic proximity. U.S. startups most closely connected to the investing VC (outside the VC's direct portfolio) exhibit the largest post-investment increases in citations, whereas being located in the same city as the investor does not. A domestic benchmark that compares East Coast VCs investing in West Coast firms shows no comparable network pattern, suggesting that syndication links matter especially in cross-border settings where other diffusion channels are weaker.

Firm-level outcomes among closely connected U.S. startups provide corroborating evidence and quantify the impact on innovative performance. Total patent output rises by about 10%, and high-quality output increases by a similar amount. Effects are larger in technologies tied to the foreign investee: patenting within the invested classes increases by 22%, and high-quality patenting by 34%. Spillovers also affect inputs and subsequent performance. The inventor base expands, with unique inventors growing by 12% overall and by 21% within invested classes, and closely connected firms are about 5% more likely to exit via IPO or acquisition within 5 years.

Taken together, the evidence indicates that independent VCs operate as international knowledge conduits. Prior syndication networks transmit ideas beyond VCs' own portfolios, raising both the quantity and the quality of innovation and improving subsequent firm performance among connected U.S. startups.

Tables

Table 1: Top 10 Foreign Countries by Deal Frequency

Country	Deal Count	Percent (%)	Cumulative (%)
Canada	167	21.52	21.52
Israel	167	21.52	43.04
United Kingdom	141	18.17	61.21
Germany	45	5.80	67.01
Switzerland	33	4.25	71.26
France	27	3.48	74.74
China(mainland)	23	2.96	77.71
Finland	22	2.84	80.54
Netherlands	16	2.06	82.60
Sweden	16	2.06	84.66

Notes: The table lists the ten most frequent foreign countries in the sample of U.S. VC cross-border deals. A "deal" is the first observed U.S. VC financing for each foreign startup (one deal per company), and countries are assigned by the investee's headquarter locations. "Percent" is the country's share of all such first-deal events over the sample period; "Cumulative" is the running total in descending order of deal count.

Table 2: Top 10 (45.17% observations) CPC Subclasses by Deal Relevancy

CPC Subclass	Name	Deal Count	Percent (%)
G06F	Electric digital data processing	93	7.37
A61K	Preparations for medical, dental or toiletry purposes	84	6.66
A61B	Medical or veterinary science	80	6.34
H04L	Transmission of digital information	71	5.63
C07K	Peptides	53	4.20
G01N	Investigating or analyzing materials	52	4.12
C12N	Microorganisms or enzymes	44	3.49
H04N	Pictorial communication	33	2.61
A61F	Filters implantable into blood vessels; prostheses; devices providing patency to, or preventing collapsing of, tubular structures of the body	30	2.38
C07D	Heterocyclic compounds	30	2.38

Note: The table lists the top ten CPC subclasses most frequently linked to deals in the sample of U.S. cross-border VC investments. A subclass is counted for a deal if the foreign investee had at least one pre-deal patent filing in that subclass. The unit of observation is deal×subclass, so a single deal may appear in multiple subclasses. "Deal Count" is the number of deals for which the subclass is relevant; "Percent" is that count divided by the total number of deal×subclass observations. For example, G06F appears in 93 deals, meaning 93 investees had pre-deal patents in G06F. The top ten subclasses together account for 45.17% of all deal×subclass observations. CPC names follow official subclass definitions.

Table 3: Sample Deal Industry and Deal Stage Shares over Time

		Industry						Deal Stage		
Year	# Deal	B2B	B2C	Energy	Healthcare	IT	Materials	Seed	Early	Later
2000	20	0.00	0.00	0.00	0.35	0.60	0.05	0.10	0.65	0.25
2001	18	0.00	0.11	0.11	0.17	0.56	0.06	0.06	0.50	0.44
2002	19	0.05	0.05	0.00	0.53	0.32	0.05	0.00	0.74	0.26
2003	18	0.11	0.00	0.00	0.44	0.44	0.00	0.11	0.67	0.22
2004	26	0.12	0.00	0.00	0.32	0.56	0.00	0.04	0.65	0.31
2005	29	0.28	0.03	0.03	0.34	0.28	0.03	0.00	0.52	0.48
2006	38	0.11	0.00	0.03	0.50	0.37	0.00	0.00	0.53	0.47
2007	35	0.11	0.00	0.09	0.43	0.37	0.00	0.00	0.63	0.37
2008	30	0.13	0.03	0.07	0.37	0.40	0.00	0.00	0.53	0.47
2009	33	0.06	0.00	0.03	0.61	0.24	0.06	0.03	0.58	0.39
2010	35	0.23	0.06	0.11	0.43	0.11	0.06	0.06	0.46	0.49
2011	47	0.04	0.04	0.04	0.53	0.34	0.00	0.04	0.43	0.53
2012	41	0.15	0.05	0.02	0.44	0.34	0.00	0.07	0.41	0.51
2013	61	0.08	0.11	0.02	0.43	0.33	0.03	0.11	0.31	0.57
2014	66	0.06	0.03	0.08	0.45	0.30	0.08	0.20	0.35	0.45
2015	80	0.05	0.09	0.04	0.44	0.35	0.04	0.14	0.41	0.45
2016	89	0.08	0.04	0.00	0.43	0.43	0.02	0.21	0.30	0.48
2017	91	0.15	0.04	0.00	0.38	0.35	0.07	0.22	0.41	0.37

Note: The table reports, by calendar year, the industry and deal-stage composition of the sample of U.S. VC cross-border deals. Column "# Deal" gives the number of sample deals in that year. Industry columns show the share of that year's deals in each PitchBook top-level sector (B2B, B2C, Energy, Healthcare, IT, Materials). Deal-stage columns show the share of that year's deals in each PitchBook stage grouping (Seed, Early, Later), where stages are collapsed into three mutually exclusive bins following PitchBook definitions. Within a given year, shares in each panel sum to one up to rounding.

Table 4: Summary of Connection Degrees for Sample Investors

Quartile	Mean	Median	Min	Max	Std	Obs	Unique Investors
1st	7.15	2.00	0	278	15.36	1,006	766
2nd	823.50	305.00	0	4,772	1,096.55	1,006	766
3rd	1,899.78	1,809.00	0	5,884	1,633.41	1,006	766
4th	166,721.10	165,517.00	133,847.00	188,559.00	11,684.96	1,006	766

Notes: The table reports summary statistics on connection levels across investor–year observations on distribution restricted to connections involving patenting firms, defined as U.S. companies that have filed at least one patent on USPTO as of 2022. Degrees are defined as: 1st = the investor's direct portfolio companies; 2nd = portfolio companies of the investor's co-investors; 3rd = portfolio companies of co-investors' co-investors; 4th = all remaining U.S. firms not in degrees 1–3. Connection degrees are constructed from pre-investment syndication ties at investor–year level. "Mean," "Median," "Min," "Max," and "Std" are computed across investor–year observations within each degree. "Obs" is the number of investor–year observations; "Unique Investors" is the count of distinct investors contributing observations.

Table 5: Aggregate Effects Results

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Main:Likelihood	Main:Ln	Placebo:Likelihood	Placebo:Ln	DDD:Likelihood	DDD:Ln
post#treat	0.0351***	0.0432***	0.00254	-0.00171	0.00254	-0.00171
	(0.00860)	(0.0118)	(0.00725)	(0.00838)	(0.00725)	(0.00838)
post#treat#main					0.0326***	0.0450***
					(0.0104)	(0.0135)
Pre-mean of the treated	0.189	0.692	0.109	0.190		
Observations	182,601	182,601	182,601	182,601	365,202	365,202
Patent FE	Y	Y	Y	Y		
Pair×Year FE	Y	Y	Y	Y		
Patent×Main FE					Y	Y
Pair×Year × Main FE					Y	Y

Standard errors are two-way clustered at patent and matched treat-control pair level

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

Note: This table reports regression results from the main and placebo difference-in-differences (DID) analyses and the corresponding triple-differences (DDD) specification. Outcomes are (i) an indicator for whether a patent receives any citation from the specified citer group in year t, and (ii) $\ln(1 + \text{number of citations})$. Pre-treatment means for the treated group refer to the average annual probability of receiving a citation and the average annual number of citations, respectively. Columns (1)–(2) use U.S. citations as outcomes; Columns (3)–(4) use the placebo outcome—citations from third countries (non-U.S., non-investee-country); Columns (5)–(6) report the DDD estimates from the stacked panel contrasting U.S. and third-country outcomes.

Table 6: Citation Responses Across VC Networks

VARIABLES	(1) Linear	(2) Linear	(3) Logit	(4) Logit
3rd VC_network	0.0146	0.0119	1.108	0.840
	(0.0118)	(0.0164)	(0.826)	(1.106)
2nd VC_network	0.00326	-0.00255	0.268	-0.0138
	(0.00854)	(0.0131)	(0.472)	(0.637)
post#3rd VC_network	-0.00110	-5.42e-05	0.258	0.282
	(0.00811)	(0.0120)	(0.684)	(0.905)
post#2nd VC_network	0.0255***	0.0378***	1.667***	2.537***
	(0.00955)	(0.0121)	(0.486)	(0.612)
Pre mean	0.0283			
Observations	599,978	537,160	18,991	12,635
Group*CitingCity*Year FE	Y		Y	
Group*CitingCity*CitingSubclass*Year FE		Y		Y

Note: This table reports changes in the likelihood that a U.S. patent cites the group k's invested foreign patent in year t. The sample is limited to U.S. patents that cite a *similar* foreign patent in the same country×CPC subclass×application-year cell, so estimates are conditional on comparable citation opportunity. post indicates years after the investee's first U.S. VC deal in cohort k. 2nd VC_network and 3rd VC_network denote the assignee's tier in the pre-investment syndication network; the omitted category is the 4th degree (all other U.S. firms with no first to third degree link), so effects are measured relative to the 4th degree. First-degree (direct portfolio) U.S. firms are excluded because of reverse causality. Columns (1) and (2) report linear-probability estimates (coefficients in percentage points), and columns (3) and (4) report logit coefficients (log-odds). "Pre mean" is the pre-treatment mean of the dependent variable in column (1). Standard errors are clustered by group k.

Table 7: Location Proximity

VARIABLES	(1) Linear	(2) Linear	(3) Logit	(4) Logit
same_city	0.0117	0.00188	0.775	0.156
	(0.0117)	(0.00694)	(0.606)	(0.552)
post#same_city	-0.00422	0.00587	-0.309	0.326
	(0.0103)	(0.00678)	(0.546)	(0.529)
Pre mean	0.0283			
Observations	659,125	652,298	148,480	129,234
Group*CitingSubclass*Year FE	Y		Y	
Group*CitingSubclass*Network*Year FE		Y		Y

Note: This table tests whether citation responses vary with geographic proximity to the investing VC. The outcome equals one if a U.S. patent cites the group k's invested foreign patent in year t. The sample is limited to U.S. patents that cite a *similar* foreign patent in the same country×CPC subclass×application-year cell, ensuring comparable technology need of the citing patents. same_city equals one when the assignee is located in the same city as the investing U.S. VC; "post" indicates years after the investee's first U.S. VC deal for group k. Columns (1)–(2) report linear-probability models; columns (3)–(4) report logit models. Fixed effects are as listed in the table. "Pre mean" is the pre-investment mean of the outcome in column (1). Standard errors are clustered by group k.

Table 8: Domestic Citation Responses Across VC Networks

VARIABLES	(1) Linear	(2) Linear	(3) logit	(4) logit
3rd degree network	0.00356	-0.000201	1.831	-0.0643
	(0.00244)	(0.00279)	(1.278)	(1.045)
2nd degree network	-0.00107	-0.000265	-1.239	-0.306
	(0.000683)	(0.000237)	(0.885)	(0.305)
post#3rd degree network	0.00199	0.00456	-0.167	1.465
	(0.00389)	(0.00484)	(1.196)	(1.149)
post#2nd degree network	-0.000809	-0.00266	-0.0661	-1.674
	(0.00121)	(0.00165)	(1.198)	(1.127)
Pre mean	0.00401			
Observations	4,568,394	4,285,713	333,633	236,502
Group k*CitingCity*Year FE	Y		Y	
Group k*CitingCity*CitingSubClass*Year FE		Y		Y

Standard errors clustered at group level

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

Note: This table tests, in a domestic benchmark, whether citation responses vary across VC network tiers when East Coast VCs invest in West Coast firms. The dependent variable equals one if a patent assigned to an East Coast entity cites the group's invested West Coast patent in year t. The sample is restricted to U.S. patents that cite a similar West Coast patent in the same CPC subclass×application-year cell, ensuring comparable technology need of the citing patents. "post" indicates years after the investee's first U.S. VC deal for group k. 2nd degree network and 3rd degree network denote the assignee's tier in the pre-investment syndication network; the omitted category is the 4th degree (all other U.S. firms with no first to third degree link), so coefficients are measured relative to the 4th degree. First-degree (direct portfolio) East Coast firms are excluded to avoid mechanical links. Columns (1) and (2) report linear-probability estimates; columns (3) and (4) report logit coefficients. Fixed effects are as listed in the table. "Pre mean" is the pre-investment mean of the dependent variable in column (1). Standard errors are clustered by group k.

Table 9: Domestic Location Proximity

VARIABLES	(1) Linear	(2) Linear	(3) Logit	(4) Logit
same_city	-0.000537	-0.000550	-0.291	-0.302
	(0.000403)	(0.000402)	(0.226)	(0.229)
post#same_city	-0.000106	-0.000164	-0.0195	-0.0493
	(0.000463)	(0.000466)	(0.257)	(0.264)
Pre mean	0.00401			
Observations	4,623,183	4,620,655	957,673	948,286
Group*CitingSubClass*Year FE	Y		Y	
Group*CitingSubClass*Network*Year FE		Y		Y

Standard errors clustered at group level

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

Note: This table tests, in a domestic benchmark, whether citation responses vary with geographic proximity to the investing VC. The dependent variable equals one if a patent assigned to an East Coast entity cites the group's invested West Coast patent in year t. The sample is restricted to U.S. patents that cite a similar West Coast patent in the same CPC subclass×application-year cell, ensuring comparable citation opportunity. same_city equals one when the assignee is located in the same city as the investing East Coast VC; post indicates years after the group's first U.S. VC deal. Columns (1) and (2) report linear-probability estimates; columns (3) and (4) report logit coefficients. Fixed effects are as listed in the table. "Pair" denotes the VC–investee group k. "Pre mean" is the pre-investment mean of the dependent variable in column (1). Standard errors are clustered by group k.

Table 10: Innovation Productivity Outcomes

VARIABLES	(1) # Patents	(2) # Patents	(3) High-Quality (Citation)	(4) High-Quality (Citation)	(5) High-Quality (Importance)	(6) High-Quality (Importance)	(7) Inventor	(8) Inventor
Panel A: Total Productions								
Post#Treat	0.110***	0.0887***	0.139**	0.0297	0.123**	0.0874***	0.113***	0.0895***
	(0.0314)	(0.0203)	(0.0630)	(0.0247)	(0.0589)	(0.0203)	(0.0280)	(0.0186)
Observations	6,572,403	5,968,267	971,516	763,767	1,919,768	1,694,263	6,962,798	6,007,973
Panel B: Productions in Foreign Investee-related Classes								
Post#Treat	0.223***	0.179***	0.484***	0.221***	0.329***	0.150***	0.214***	0.172***
	(0.0399)	(0.0290)	(0.0973)	(0.0605)	(0.0802)	(0.0386)	(0.0404)	(0.0288)
Observations	1,229,459	1,101,884	111,488	80,743	336,827	287,709	1,220,468	1,094,813
Company FE	Y	Y	Y	Y	Y	Y	Y	Y
Cohort*Industry*PrePat*Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Control	Y	-	Y	-	Y	-	Y	-
City*Year FE	N	Y	N	Y	N	Y	N	Y

Standard errors clustered at company and cohort level

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

Notes: This table reports PPML estimates of the change in (i) total patent output (# Patents), (ii) high-quality output measured by citation-weighted and importance-weighted counts, and (iii) the number of unique inventors following U.S. VC cross-border investments. Panel A reports aggregate effects across all technologies; Panel B restricts to "invested classes," defined as the patent classes previously patented by the foreign investee companies. Columns (3)–(6) use quality measures that require observing outcomes five years after the filing year. Because we observe filings up to five years after each deal year and the sample includes deals through 2017, these columns are estimated only for deals in 2012 or earlier to maintain a balanced five-year window, which reduces the sample relative to the full-sample specifications in columns (1)–(2) and (7)–(8). Fixed effects are shown in the table. Standard errors are clustered at company and cohort level.

Table 11: Firm Success

VARIABLES	(1) Main	(2) Main	(3) Placebo	(4) Placebo
2nd degree connection	0.0120***	0.0136***	0.00395	0.00654
	(0.00437)	(0.00501)	(0.0113)	(0.0145)
Sample Mean	0.251	0.251	0.255	0.255
Observations	13,528,022	13,528,022	203,944	203,944
Investor FE	Y	Y	Y	Y
FE1	Y		Y	
FE2		Y		Y

Standard errors clustered at company and cohort level

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

This table reports differences in exit likelihood between second- and third-degree connected firms within cohorts. Columns (1)–(2) report the main estimates, and columns (3)–(4) present the placebo results. Investor FE controls for each firm's most recent direct VC investors. FE1 includes cohort × industry × first VC deal year × first VC deal type fixed effects, while FE2 additionally controls for pre-patent category. In the placebo regressions, first VC deal year is grouped into quartiles to avoid over-saturation given the smaller sample size; results remain qualitatively similar without this adjustment. Standard errors are two-way clustered at the firm and cohort level.

Table 12: Firm Success: Heterogeneity

	(1)	(2)	(3)	(4)
VARIABLES	By Sector	By Sector	By network strength	By network strength
Is 2nd degree	0.00955**	0.0105**		
	(0.00459)	(0.00530)		
same_sector	-0.000111	-0.0114		
	(0.00711)	(0.00973)		
Is 2nd degree#same_sector	0.00701**	0.00874**		
	(0.00324)	(0.00377)		
2nd degree higher qual			0.0162***	0.0165**
			(0.00612)	(0.00702)
2nd degree lower qual			0.00895**	0.0115***
			(0.00352)	(0.00408)
Sample Mean	0.251	0.251	0.251	0.251
Observations	13,528,022	13,528,022	13,528,022	13,528,022
Investor FE	Y	Y	Y	Y
FE1	Y		Y	
FE2		Y		Y

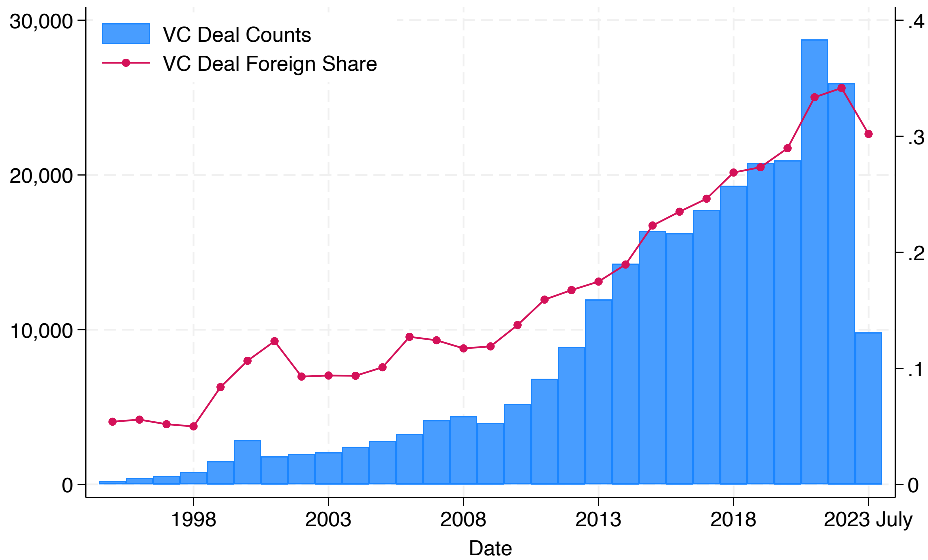
Standard errors clustered at company and cohort level

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

This table reports heterogeneity in the difference in exit likelihood between second- and third-degree connected firms within cohorts, across (i) sector overlap and (ii) network quality. Columns (1)–(2) compare effects for firms in the same sector as the foreign investee versus other sectors. Columns (3)–(4) compare higher- versus lower-quality second-degree connections; estimates are reported relative to third-degree connections (omitted category). The fixed effects mirror Table 11. Investor FE controls for each firm's most recent direct VC investors. FE1 includes cohort × industry × first VC deal year × first VC deal type fixed effects; FE2 additionally includes pre-patent category. Standard errors are two-way clustered at the firm and cohort levels.

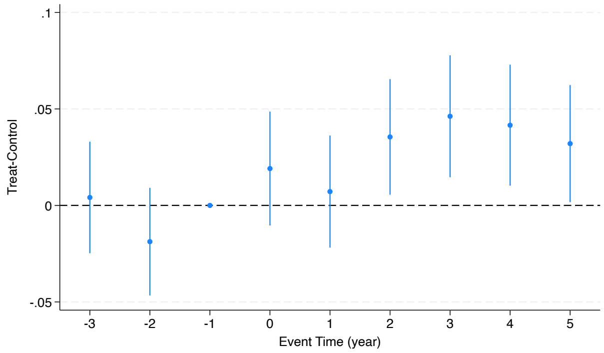
Figures

Figure 2: Time Trend of U.S. Cross-border VC Deals

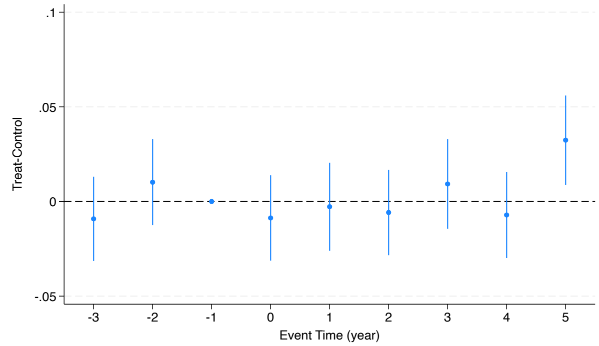


Notes: Data used to produce this figure comes from Pitchbook. Bars show the annual count of total number of U.S. VC deals (left axis). The line with markers reports the fraction of these deals that are cross-border, defined as investments in portfolio companies headquartered outside the United States at the time of the deal (right axis). The final point corresponds to July 2023.

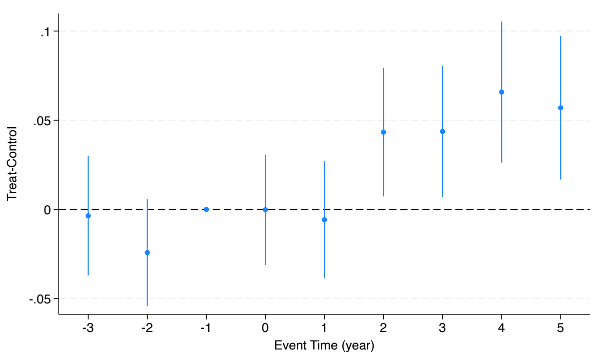
Figure 3: Aggregate Analysis: Dynamics



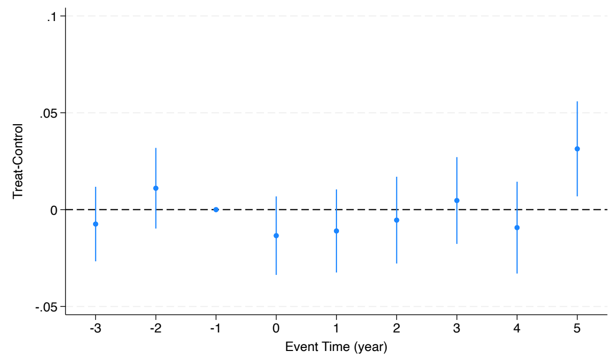
Panel A: US Citation Likelihood



Panel B: Placebo Citation Likelihood



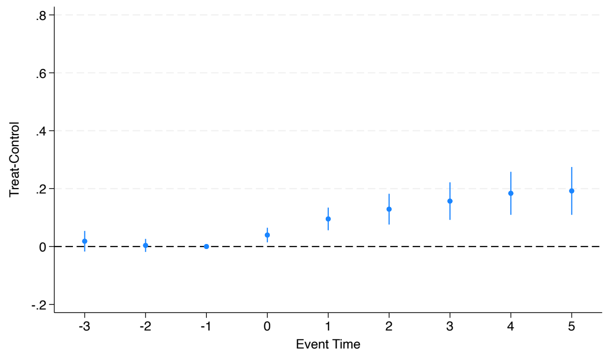
Panel C: Ln(1+US Citations)



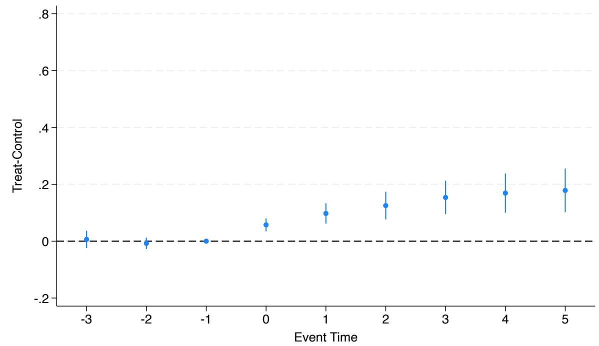
Panel D: Ln(1+Placebo Citations)

Notes: The figure plots event-study estimates of the treated–minus–control difference in U.S. citations around the treatment (sample cross-border VC deal), as in Equation 2. Panels A and B show the probability of at least one U.S. citation for the main and placebo samples, respectively; Panels C and D show $\ln(1 + \text{U.S. citations})$ for the main and placebo samples.

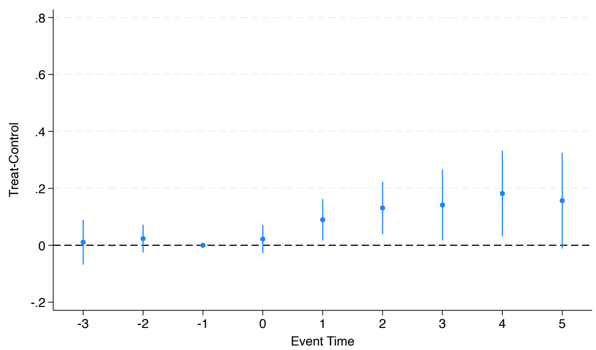
Figure 4: Total Innovation Activity



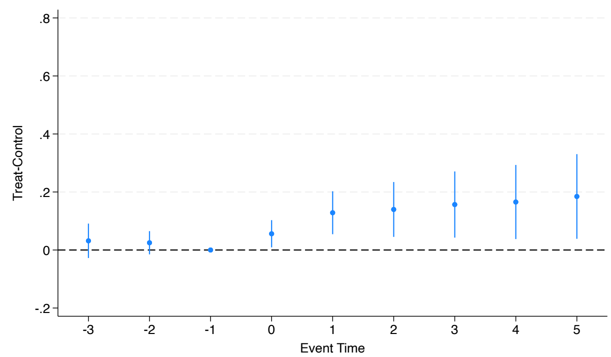
Panel A: Total Patent Productions



Panel B: Number of Unique Inventors



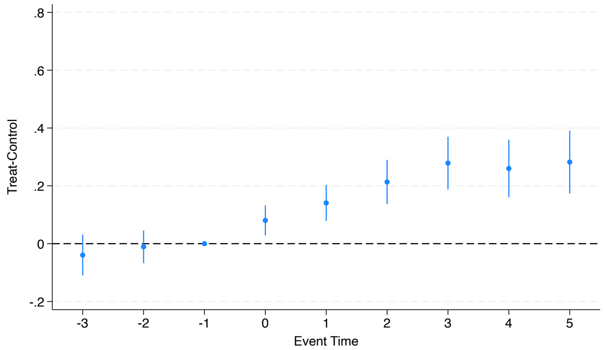
Panel C: High-quality Patents (Citation)



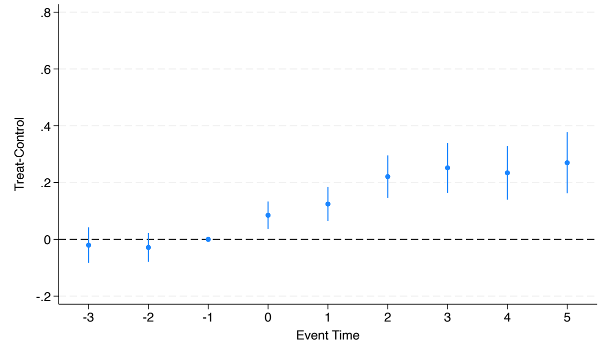
Panel D: High-quality Patents(Importance)

Notes: The figure plots event-study estimates of treated–minus–control differences in firm-level innovation around treatment (sample cross-border VC deal). Treated firms are second-degree startups in the investing VC's pre-investment syndication network; controls are third-degree startups. Panel A shows total patent output. Panel B shows inventor participation (the number of unique inventors on the firm's USPTO patents). Panel C reports high-quality patent output, defined as the count of the firm's patents in the top half of five-year forward citations within CPC subclass×application-year. Panel D reports an alternative quality metric using the Kelly et al. (2021) importance measure and counts the firm's patents that rank in the top half within their CPC subclass×application-year.

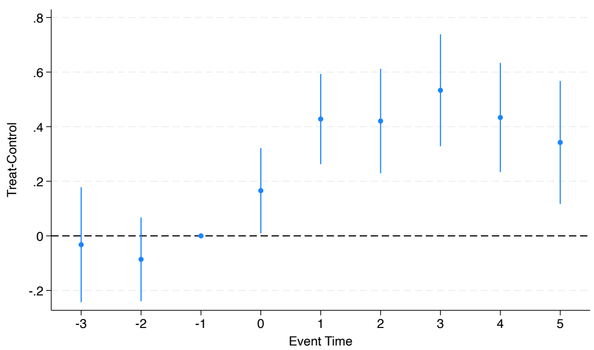
Figure 5: Innovation Activity in Invested Classes



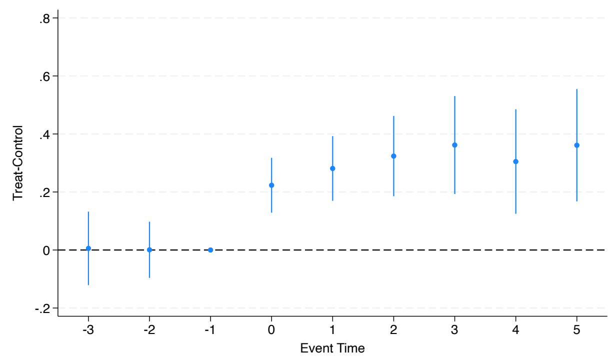
Panel A: Total Patent Productions



Panel B: Number of Unique Inventors



Panel C: High-quality patents (Citation)



Panel D: High-quality patents (Importance)

Notes: The figure plots event–study estimates of treated–minus–control differences in firm-level innovation *within invested patent classes* around treatment (the sample cross-border VC deal). Treated firms are second-degree startups in the investing VC's pre-investment syndication network; controls are third-degree startups. Panel A shows patent output within the cohort's invested CPC subclasses. Panel B shows inventor participation (the number of unique inventors on the firm's USPTO patents) within those subclasses. Panel C reports high-quality patent output within those subclasses, defined as the count of the firm's patents in the top half of five-year forward citations within CPC subclass×application-year. Panel D reports an alternative quality metric using the Kelly et al. (2021) importance measure and counts the firm's patents that rank in the top half within their CPC subclass×application-year.

Appendix A. Additional Result Tables

Table 13: Citation Responses Across VC Networks: Robustness

	(1)	(2)	(3)	(4)
VARIABLES	Linear	Linear	Logit	Logit
3rd VC_network	0.0232	0.0145	1.123	0.685
	(0.0215)	(0.0271)	(0.951)	(1.222)
4th VC_network	0.00456	-0.00491	0.298	-0.148
	(0.00893)	(0.0125)	(0.411)	(0.569)
post#3rd VC_network	0.00219	0.00433	0.531	0.599
	(0.0150)	(0.0192)	(0.792)	(0.953)
post#4th VC_network	0.0192**	0.0298**	1.137***	1.855***
	(0.00835)	(0.0122)	(0.423)	(0.613)
Pre-mean	0.0475			
Observations	369,450	339,427	25,385	20,103
Group*CitingCity*Year FE	Y		Y	
Group*CitingCity*CitingSubclass*Year FE		Y		Y

Standard errors clustered at group k level

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

Note: This table replicates the network analysis with an alternative conditioning set. The outcome equals one if a U.S. patent cites the group's invested foreign patent in year t. The sample is restricted to U.S. patents that cite a similar foreign patent in the same country-CPC subclass×application-year cell, and whose cited patent's grant year differ by within ±1 year of the group's invested patent's grant year. "post" indicates years after the group's first U.S. VC deal. 2nd VC_network and 3rd VC_network indicate the assignee's pre-investment network tiers; the omitted category is 4th VC_network, so coefficients are measured relative to the fourth degree.. Columns (1)–(2) report linear-probability models; columns (3)–(4) report logit models. Standard errors are clustered by group k.

Table 14: Location Proximity: Robustness

	(1)	(2)	(3)	(4)
VARIABLES	Linear	Linear	Logit	Logit
same_city	0.0182	0.000922	0.734	0.0492
	(0.0192)	(0.0101)	(0.616)	(0.530)
post#same_city	-0.00676	0.0104	-0.314	0.377
	(0.0174)	(0.0105)	(0.573)	(0.526)
Pre-mean	0.0475			
Observations	397,836	394,294	114,605	100,273
Group*CitingSubclass*Year FE	Y		Y	
Group*CitingSubclass*Network*Year FE		Y		Y

Standard errors clustered at cohort level

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

Note: This table replicates the location–proximity analysis using an alternative conditioning set. The outcome equals one if a U.S. patent cites the group's invested foreign patent in year t. The sample is restricted to U.S. patents that cite a similar foreign patent in the same country$\times$CPC subclass$\times$application-year cell and whose cited patent's grant year is within ± 1 year of the group's invested patent's grant year. same_city equals one when the assignee is located in the same city as the investing U.S. VC; post equals one for years after the group's first U.S. VC deal. Columns (1) and (2) report linear-probability models; columns (3) and (4) report logit models. "Pre mean" is the pre-investment mean of the outcome in column (1). Standard errors are clustered by group k.

Table 15: Innovation Productivity Outcomes: Extensive Margin

VARIABLES	(1) Raw	(2) Raw	(3) High-Quality (Citations)	(4) High-Quality (Citations)	(5) High-Quality (Importance)	(6) High-Quality (Importance)
Panel A: Total Productions						
Post#Treat	0.0165***	0.0175***	0.0111***	0.00996***	0.0105**	0.0121***
	(0.00379)	(0.00328)	(0.00233)	(0.00196)	(0.00416)	(0.00349)
Pre-mean of treated	0.373	0.373	0.147	0.147	0.260	0.260
Observations	10,713,213	10,713,095	3,944,250	3,944,159	3,900,834	3,900,709
Panel B: Productions in Foreign Investee-related Classes						
Post#Treat	0.00533***	0.00526***	0.00156***	0.00143***	0.00360***	0.00301***
	(0.000517)	(0.000482)	(0.000275)	(0.000264)	(0.000571)	(0.000528)
Pre-mean of treated	0.0469	0.0469	0.0122	0.0122	0.0253	0.0253
Observations	9,869,823	9,869,734	3,806,811	3,806,729	3,791,862	3,791,778
Company FE	Y	Y	Y	Y	Y	Y
Cohort*Industry*PrePat*Year FE	Y	Y	Y	Y	Y	Y
Control	Y	-	Y	-	Y	-
City*Year FE	-	Y	-	Y	-	Y

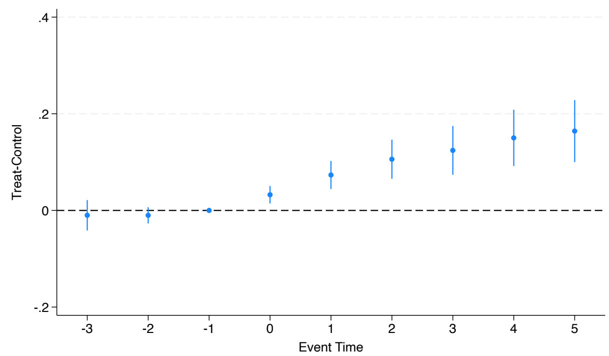
Robust standard errors in parentheses

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

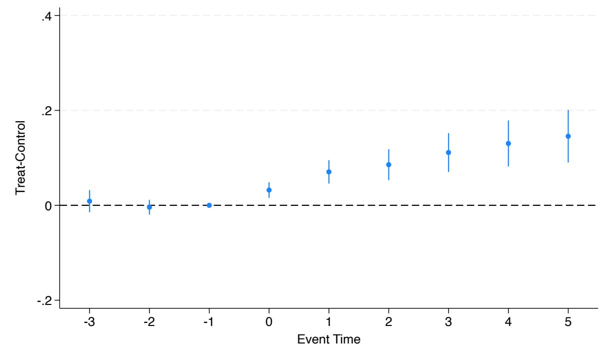
Notes. This table re-estimate the designs from Sections 4.1 and 4.2 using binary outcomes to probe the extensive margin: $\mathbf{1}\{\text{Produce Patent}\}_{i,k,t}$ and $\mathbf{1}\{\text{Produce High-Quality Patent}\}_{i,k,t}$, estimated by OLS (linear probability models). “Q1” and “Q3” denote the two high-quality definitions (citation-weighted and importance-weighted, respectively). The Post×Treat coefficient captures the change in the probability of patenting in different categories following the investment. Standard errors are clustered at company level.

Appendix B. Additional Result Figures

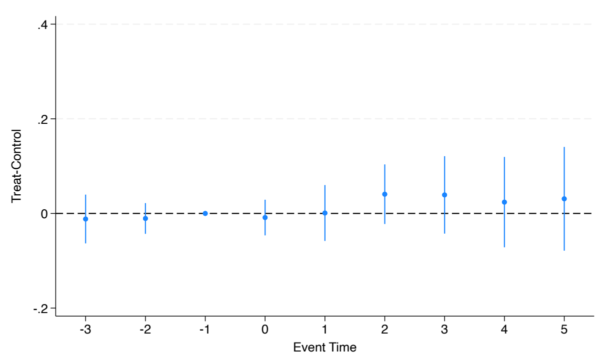
Figure 6: Total Innovation Activity: with City*Year Fixed Effects



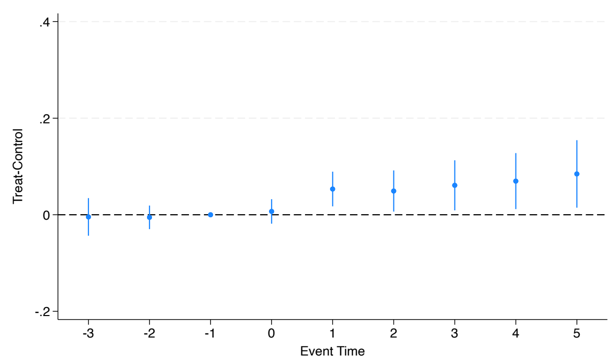
Panel A: Total Patent Productions



Panel B: Number of Unique Inventors



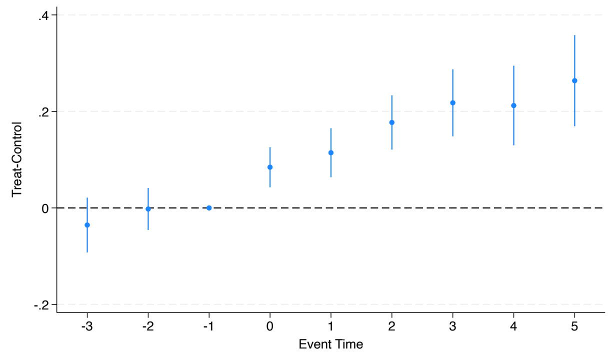
Panel C: High-quality Patents (Citation)



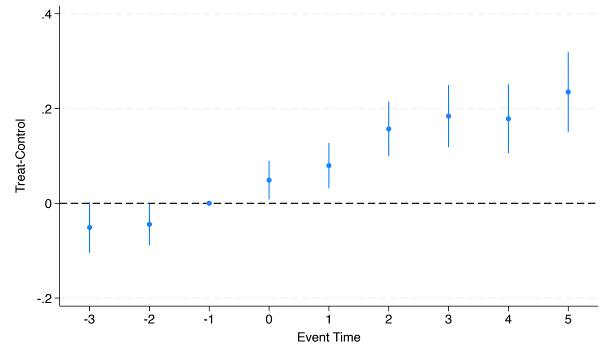
Panel D: High-quality Patents(Importance)

Note: Note: This figure reports dynamic DID estimates of total innovation outcomes, using the specification in Equation 7. Unlike Figure 4, which includes city×year controls, this figures present estimates from using city×year fixed effects to absorb location-specific innovation trends. Panel A shows changes in the number of patents produced. Panel B displays the number of unique inventors within each company who filed patents over time. Panel C illustrates changes in patent quality, defined as the number of patents falling in the top half of their CPC class and application year based on five-year forward citation counts. Panel D reports patent quality using the "Importance" measure introduced in Kelly et al. (2021), counting patents in the top half of their CPC class in the same application year. The scale of the graphs is aligned with the subsequent figure (Figure 5), which shows the same outcomes for patent classes relevant to the VC investments, for easier comparison.

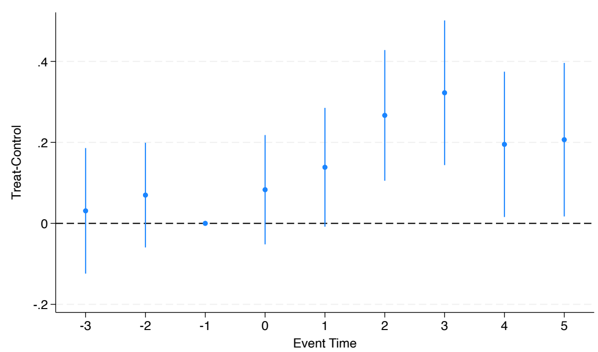
Figure 7: Innovation Activity in Invested Classes: with City*Year Fixed Effects



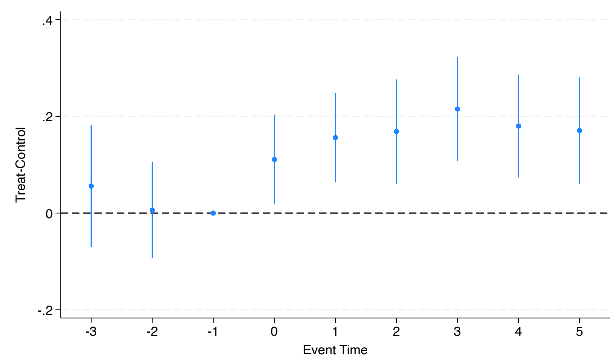
Panel A: Total Patent Productions



Panel B: Number of Unique Inventors



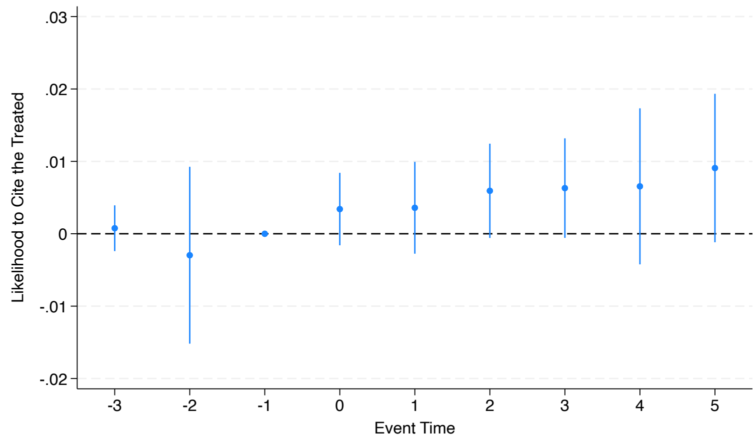
Panel C: High-quality patents (Citation)



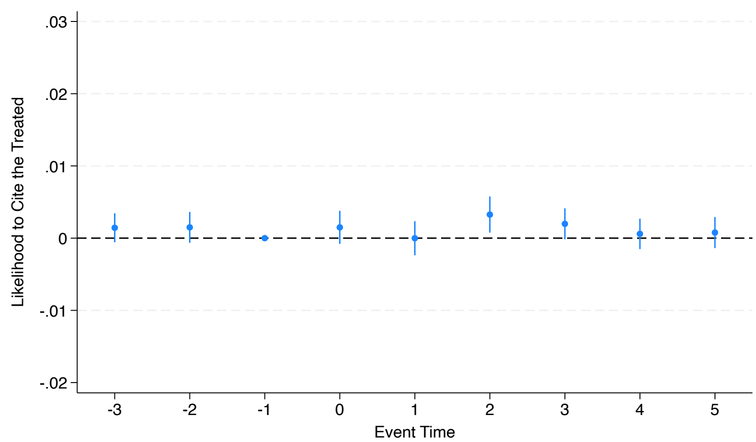
Panel D: High-quality patents (Importance)

Note: This figure reports dynamic DID estimates of innovation outcomes within investee-related classes, using the specification in Equation 7. Unlike Figure 5, which includes city×year controls, this figures present estimates from using city×year fixed effects to absorb location-specific innovation trends. Panel A shows changes in the number of patents produced. Panel B displays the number of unique inventors within each company who filed patents over time. Panel C illustrates changes in patent quality, defined as the number of patents falling in the top half of their CPC class and application year based on five-year forward citation counts. Panel D reports patent quality using the "Importance" measure introduced in Kelly et al. (2021), counting patents in the top half of their CPC class in the same application year.

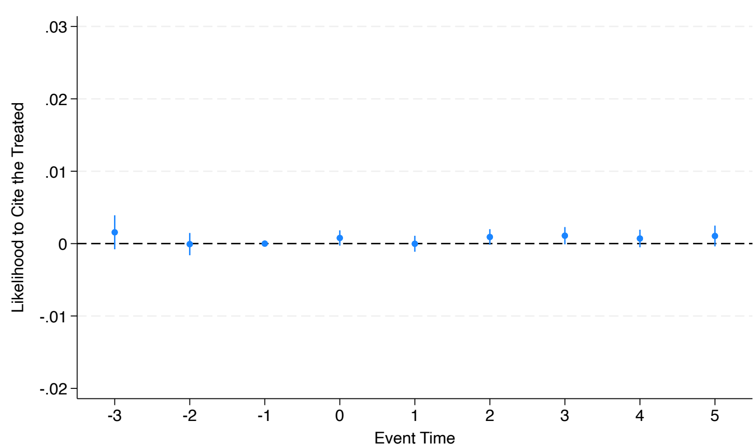
Figure 8: Event study by VC network distance (2nd, 3rd, and 4th degree)



(a) 2nd-degree network



(b) 3rd-degree network



(c) 4th-degree network

Notes. The figure stacks three event-study panels showing how the likelihood that a U.S. patent cites the treated foreign patent changes around the event, *conditional on the U.S. patent citing a comparable foreign patent in the same year*. Panels (a)–(c) report results separately for 2nd-, 3rd-, and 4th-degree network distance (2nd = closest, 4th = farthest). Dots are event-time coefficients relative to the pre-event reference period; vertical bars are 95% confidence intervals.

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