Fencing Off Silicon Valley: Cross-Border Venture Capital and Technology Spillovers

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Abstract

The treatment of foreign investors is a contentious topic in U.S. entrepreneurship policy. We model a setting where foreign corporate investments in Silicon Valley may allow U.S. entrepreneurs to pursue technologies that they could not otherwise, but may also lead to knowledge spillovers. We show that despite the benefits from such inbound investments for U.S. firms, it may be optimal for the U.S. government to raise their costs to deter these investments. Using as comprehensive as possible a sample of investments by foreign corporate investors in U.S. startups, we find evidence consistent with the presence of knowledge spillovers to foreign investors.

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1 Introduction

One of the most contentious issues in public policy regarding U.S. entrepreneurship over the past half-decade has been the treatment of foreign investors. The military community (see, for instance, Brown and Singh, 2018; U.S. House, Permanent Select Committee on Intelligence, 2018; and U.S. Senate, Committee on Banking, Housing, and Urban Affairs, 2018) has highlighted the extent of foreign venture investments in Silicon Valley, particularly from Chinese corporations, individuals, and financial institutions. These analysts have also emphasized that these investments are often in critical areas, such as artificial intelligence, fintech, robotics, and virtual reality, and expressed the fear that these activities may be leading to technology flows that, while legal, are nonetheless detrimental to U.S. economic and military interests. Particular concerns surround corporate venture investments, since these investors are well-suited to gain insights from their interactions with the companies in their portfolios and to exploit these discoveries: Brown and Singh (2018) highlight, for instance, Alibaba's and Enjoyor's investments in Magic Leap, Baidu's purchase of shares in Velodyne, and Lenovo and Tencent's investments in Meta (now Campfire), companies that specialized in areas such as augmented reality, active remote sensing, and artificial intelligence.

The primary policy response to these concerns has been to strengthen the mandate of the Committee on Foreign Investment in the U.S. (CFIUS).[1] President Gerald Ford established CFIUS by executive order in 1975, an era of concern about Japanese purchases of American technology firms. The mandate of the inter-agency working group was to review national security implications of foreign investments in U.S. companies or operations. Its powers have been strengthened by a series of laws, especially the Exon-Florio Amendment in 1988, the Foreign Investment and National Security Act of 2007, and the Foreign Investment Risk Modernization Act of 2018. The latter act expanded the scope of CFIUS to include reviews of "non-controlling 'other investments' that afford a foreign person an equity investment in and specified access to information... [about] certain critical technologies." This legislation, and in particular the enabling regulations promulgated by the U.S. Department of Treasury (2019), raised substantial concerns among the U.S. venture capital community (National Venture Capital Association, 2019). Despite the new rules, Chinese investments in U.S. ventures remain robust (Hanemann et al., 2021). Similar controversies have played out contemporaneously in, among other nations, Australia, Canada, Germany, Israel, and the United Kingdom (Klein, 2018).

Despite the intense controversy and substantial stakes, the attention of economists to these issues has been very modest. While academics have scrutinized numerous aspects of entrepreneurial finance, such as the mixture of securities employed and the consequences of intensive monitoring by investors, the impact of cross-border capital flows on technology transfer have received almost no attention.[2] The focus of the few examples has exclusively been the performance of the host country

[1] This brief history is based primarily on Masters and McBride (2019).

[2] Perhaps the most related (though still quite distant) papers in this literature are studies of the rationales of corporations to initiate venturing programs (Ma, 2020) and the propensity of venture-backed firms to enter into strategic alliances with other portfolio firms (González-Uribe, 2020; Lindsey, 2008).

(e.g., Alfaro et al., 2004), with some recent prominent examples establishing a causal link between foreign direct investment and the productivity of the recipient firm (Fons-Rosen et al., 2021) or other firms in the same sector (or in upstream sectors) that benefit from knowledge spillovers (Fons-Rosen et al., 2017). However, the technology transfer to the country providing cross-border funds has remained largely unexplored. Nor has this been a major focus of works on trade and innovation. In Shu and Steinwender's (2019) review of the theoretical and empirical economics literature studying the link between trade liberalization and firms' innovation-related outcomes, the authors examine four types of trade shocks: import competition, export opportunities, access to foreign inputs (intermediate goods or foreign labor), and foreign input competition. The authors highlight that there has been virtually no literature looking at the consequences of foreign competition for inputs such as R&D and early-stage innovation.

This paper seeks to address this gap, examining foreign corporate investment in Silicon Valley from a theoretical and empirical perspective. We begin with a stylized model of two countries, which builds on the step-by-step innovation framework of Schumpeterian creative destruction models.[3] This class of models provides a natural setting to study product market competition between firms and its dynamic effect on their innovation decisions (Akcigit and Ates, 2021). We extend this framework to an open-economy setting, in which competition happens between firms of two nations, and, in a novel application, we introduce financing decisions for firms. This setting allows us to focus on how foreign corporate venture capital (CVC) financing interacts with forward-looking firms' dynamic innovation efforts. As such, this new theory speaks to the nexus between international technological competition and cross-border investment.

In our setting, there is a variety of industries in each country, with one incumbent in each. These firms differ in their labor productivity and engage in Bertrand competition. In each nation, startups that are potentially more productive may appear, in which case they will replace the incumbent firm. To be successful, however, these new firms must raise financing. In some cases, this financing may not be available domestically.

One option that entrants face is to seek money from foreign corporate investors—a distinctive feature of our framework. Such financing is "good news" for the entrant firm, as without financing it may not be able to put its superior technology into practice. But it may also lead to spillovers to the overseas firm providing the financing and the nation where it is based. In some cases, these spillovers may lead to a serious national security threat to the nation that is the home of the startup, resulting in significant public expenditures to protect against the threat from the foreign nation. In the model, we include a cost term to capture these potential security concerns. While startups may not pay attention to the national security consequences of their funding sources, policy makers do internalize these consequences, facing a trade-off between the abundance of innovation financing and security concerns.

[3]The step-by-step innovation framework has been developed by Aghion et al. (1997, 2001, 2005). For recent applications, see Acemoglu and Akcigit (2012), Akcigit et al. (2018) and Akcigit and Ates (2021).

We posit that in response to these concerns, policymakers can raise the cost of foreign financing, whether through regulatory barriers or taxes. If these costs are high enough, these costs will choke off venture investments by foreign corporations. But startups with the potential to enhance domestic productivity may consequentially languish unfunded.

In a version that is reasonably disciplined by the micro- and macro-level data, we explore the dynamics of the equilibrium in this model to differences in the relative technological positioning of the leader and follower incumbent firms. This exercise yields a number of testable predictions. When the following incumbent is lagging far behind, it is more likely to engage in cross-border investments. As the two firms become more similar in their productivity, the probability of cross-border investment activity approaches zero. The probability of investment is also a function of the baseline level of spillovers that would have occurred without any foreign venture investment. In particular, higher levels of baseline spillovers reduce the gains from the investment and dampen the incentive of foreign incumbents to invest abroad.

In a numerical example, we seek to explore the optimal response by policymakers. We depict the government in the country with technological leadership as being able to raise the cost of foreign corporate investments. We posit that in its deliberations, policymakers consider not only the impact of these investments on the prospects for domestic firms, but also the potential for an "arms race" if a foreign nation has the potential to acquire leadership in a critical technology. As the threat of military competition grows, the exercise suggests that the optimal cost imposed on foreign corporate venture investors should increase. At the same time, it should be noted that the hypothesized cost of technological competition is very substantial, suggesting that such cost-raising interventions should not be undertaken casually.

To sum up, the theoretical model and the numerical exercise help us uncover key aspects of a complicated dynamic problem featuring foreign venture investments and firms' forward-looking innovation decisions. This approach also allows us to reflect on policy implications in a manner that a purely descriptive empirical study could not. With a number of testable predictions from this analysis in hand, we next explore these ideas empirically, to see whether we find evidence supportive of the model.

We build a data-set of venture investments that includes as comprehensive a sample of investments by non-U.S. corporate investors in U.S. startups as possible. We identify transactions involving 344 companies from 32 distinct countries between 1976 and 2015. We identify the patents of the startup firms, as well as patenting by the corporate investors specifically and by residents of the countries in which they are based.

In our initial analysis, we examine patenting activity before and after the corporate investment. We show that around the time of investment, patent applications by entities in the country in which the investor is based increase in the patent classes that the startup focuses on. We also show that citations by entities in the country in which the investor is based increase in the same patent classes. Moreover, at a more micro level, we show that the foreign corporations that invest

in U.S. startups increase their own rate of citations to those U.S. startups after investing. The results, consistent with the analysis of domestic CVC investors by Ma (2020), suggest that there are benefits from these investments in the form of knowledge spillovers.

The results are also heterogeneous in a way consistent with the theoretical framework. In particular, these effects are stronger in patent classes that are more basic, where catching up to the technological frontier without the benefit of the insights gained through a corporate venture investment is likely to be harder. These investments are more common when the nation in which the corporation is based is further behind the United States in the given technology, measured in various ways. The investments appear to be responses to address this technology gap, at least partially. When we look at investments by Chinese corporations specifically, we see that the coefficients suggest that their investments are associated with two-to-three times more spillovers than foreign corporate venture capital in the sample as whole.

We finally examine the consequences of these investments. More foreign investments in firms specializing in a technology class are associated with more subsequent patenting by U.S. startups in this class. These results are at least consistent with the hypothesized benefits of such investments in easing capital constraints.

Taken together, these empirical results seem to suggest the reasonableness of many of the assumptions behind the model. Corporate venture investments may allow companies and nations to catch up, at least when they are not too far behind the technological leaders. More generally, the combination of our approaches suggests the power of a broad-based approach: the model helps map out the complex dynamics at play, the calibration suggests potential magnitude of these effects, and the empirical analysis provides support for some of the key assumptions behind the model.

To be sure, the empirical analysis has its limitations. While a number of papers seeking to explore the impact of venture investments on innovation have sought to exploit exogenous shifts, such as pension fund reforms and changes in commercial flight schedules (Kortum and Lerner, 2000; Bernstein et al., 2016), identifying similar shifts in foreign corporate investments that are uncorrelated with key dependent variables is exceedingly difficult. Thus, the results must be interpreted more as suggestive that the trade-offs illustrated in the model seem reasonable. In addition, we only examine the impact of one mechanism for knowledge flows, foreign corporate venture investments, and not other channels as the flow of researcher across borders, other forms of foreign direct investments, and academic collaborations.

There has been a long literature on endogenous growth and innovation, dating back to Romer (1990) and Aghion and Howitt (1992). This framework we use in our analysis is most closely related to Aghion et al. (2001, 2005), in that it builds on the step-by-step innovation framework pioneered by these studies. An important feature of this framework is that it captures the relationship between competition among firms and their productive investments—firms' innovation incentives depend on how close they are to their rivals in the technological race. The novel feature of our framework is that it focuses on VC investments by foreign corporations and explicitly models the interplay

between technological differences across competing firms and their incentives to invest abroad.

While our focus is over a broad span of countries over multiple decades, this paper is also related to the extensive literature on Chinese industrial policy in recent years (and earlier Japanese policies). Examples of this literature, from differing perspectives, include Barwick et al. (2019), Bown (2019), and Branstetter et al. (2017).

The plan of this paper is as follows. Part 2 provides some motivating examples to fix the ideas. Parts 3 and 4 lay out the theory along with a numerical example. Part 5 describes our empirical analysis. The final section concludes the paper.

2 Motivating examples

The U.S. defense and intelligence community have identified many examples where technology with national security implications has moved from U.S. start-ups to national defense-affiliated firms abroad, particularly in China. There are, of course, many mechanisms through which these knowledge flows can take place, including the return of entrepreneurs to their home country, university collaborations and the like. But numerous accounts that corporate venture capital investments have been an important mechanism for these knowledge flows.

A recent U.S. Department of Defense (DoD) report (U.S. Department of Defense, Protecting the National Security Innovation Base Study Group OSE/Factor 8 Program, 2022) highlighted knowledge flows from young firms that had received grants as part of the DoD Small Business Innovation Research program (the largest U.S. public venture program). The report highlighted the extensive tracking of DoD SBIR awards by a Chinese military-affiliated research institution, which used publicly disclosed to identify start-ups working in defense-relevant technology "hot spots." Several case studies illustrated the ways in which foreign corporate investments were associated with subsequent knowledge flows. Two examples were as follows:

- Skyline Software Systems is a Virginia-based company formed in 1997 that uses earth visualization software to create interactive, photo-realistic 3D environments. The technology has a variety of civilian uses, such as planning utility lines and mining projects. But an important set of applications related to defense, where it is used for activities including mission planning and rehearsal, tracking individuals and equipment in the field, and Unmanned Aerial Vehicle operations. The company has received extensive funding from the U.S. Army, among other defense agencies. In 2013, the company received funding from PRC-based company Terra IT Technology Co., also known as Tairui Shu Chuang Ke (Beijing) Co., Ltd. In the same year, Skyline Software Systems president attended a developer conference in Beijing, "Integration and Innovation, Win-Win Cooperation." Today, its Chinese partner displays Skyline's technology on its website, under the heading of "military and national defense."

- LumosTech Inc was formed in February 2016 to develop a sleep mask that alters the user's circadian rhythm to enhance adaptation to challenging environments. The company received funding from the National Space Biomedical Research Institute (which included work with former and perhaps current NASA personnel) in 2016 and the DoD (through the U.S. Special Operations Command) in 2019. The company subsequently received funding from Oriza Ventures, a venture capital fund based in Santa Clara, California that is a subsidiary Suzhou Oriza Holdings Co., Ltd., a major state-owned investment conglomerate. Oriza Ventures has invested approximately US $2.7 billion in U.S. startups from 2001 to 2018. It has two dedicated funds that support participants in the Thousand Talents Start-up Contest. This annual Silicon Valley competition, an offshoot of China's major talent program, gives entrepreneurs the chance to find investment backing from Chinese firms and encourages them to establish operations in China.

Other accounts suggest that in numerous cases, firms have turned to Chinese corporate venture financing due to a lack of interest by U.S. venture funds. The experience of Kateeva illustrates this issue. The firm was established in 2008 by three post-doctoral students, Conor Madigan, Gerry Chen, and Valerie Gassend, as a spin-off of federally funded MIT research from the laboratory of Professor Vladimir Bulovic on organic light-emitting diodes (OLEDs).[4] While this technology, which placed a layer of organic materials between two electrodes on a substrate, dated back to the 1950s, Kateeva's manufacturing techniques represented a dramatic step forward. The company soon moved to Silicon Valley, and raised three rounds of venture financing from well-regarded U.S. venture groups such as Sigma Partners and Spark Capital. The investors were attracted to the potential of the firm to improve existing products, from LED television screens to cell phone displays, and ultimately build nanostructure circuits and luminescent concentrators. OLED is also used in a growing number of military applications, such as supporting soldiers, pilots, and divers, among others, in field operations, depicting thermal imaging, and training.

By 2013, however, the venture investors were growing impatient, as the company was taking longer and requiring more capital to generate revenue than originally anticipated. Moreover, the interest of venture capitalists was rapidly shifting to software-based businesses, as the outsized success of companies from Pinterest to Uber caught their attention. As Alain Harrus, a seasoned technology executive and venture investor who served as CEO from 2013 to 2020 noted, to many potential investors, "the idea of creating an independent, U.S.-based, global equipment manufacturer for the display industry in the 21rst century, where 100% of the manufacturing plants are located in south east Asia, seem[ed] preposterous" (Harrus, 2020). Nonetheless, Kateeva was buoyed by a major order from Samsung and survived this initial financing disruption.

[4]This account is drawn from a conversation with Alain Harrus along with other sources:
https://www.eecs.mit.edu/news-events/media/madigan-bulovic-create-kateeva-mass-produce-oled-displays,
https://www.crunchbase.com/organization/kateeva,
https://www.iam-media.com/finance/troubled-us-startup-pledges-patents-chinese-backer,
https://www.nytimes.com/2017/03/22/technology/china-defense-start-ups.html,
http://www.kateeva.com/.

Despite its technological and product market successes, Kateeva proved extremely challenging to sustain. A crucial problem was the need for substantial funding, both for capital expenditures and working capital. In 2016, the firm raised $88 million, primarily from Chinese investors. The financings were led by two corporate venture investors and Kateeva customers, BOE Display and TCL, as well as Redview Capital, a spinoff of a firm run by the former Chinese premier Wen Jiabao's son, Wen Yunsong.

While the firm planned to go public on the NASDAQ, the proposed offering was withdrawn in the face of unfavorable industry conditions in 2018. In late 2019, Kateeva faced a severe liquidity crunch.[5] To avoid bankruptcy, the firm borrowed $15 million from a Chinese finance firm, which triggered a shift in the control of the board to Chinese investors. The ensuing restructuring saw layoffs and a major exodus of the original executive team. It is anticipated that post-pandemic, the firm will move much of its manufacturing from the US to China and ultimately list on Shanghai's STAR market.

3 A Model with Endogenous Markups and Innovation

Our model economy consists of two countries and a unit measure of industries, with the final product of each industry being consumed by representative households. Each industry is characterized by a duopoly, with one firm from each country. The industry output is a CES combination of the two varieties they produce, which can be traded freely across borders. The firms produce essentially the same variety but with different labor productivities and compete à la Bertrand. As a result, both producers are actively producing imperfectly substitutable goods, and their profits, markups, and market shares are a function of their productivities relative to the one of their competitors. These relative productivity levels also evolve endogenously, as new startups from each country replace domestic incumbent firms with new, more efficient production techniques—reflecting the essence of "step-by-step innovations" framework.

In each country, new startups are born from business ideas that arrive at an exogenous rate. Each idea needs financing for it to be implemented and give rise to a new firm. To capture the essence of cross-border corporate venture capital financing, we allow incumbent firms to invest in the ideas generated in the other country by paying a one-time investment cost. Upon a successful investment, the investor obtains a claim on a portion of the profits that is generated by the new foreign startup, which enters the same industry replacing the foreign incumbent. Moreover, the domestic incumbent derives knowledge spillovers from the new idea implemented by the emerging startup. This new channel of foreign investment will be the focus of our analysis.

[5] https://www.displaydaily.com/article/display-daily/despite-offering-the-best-ijp-tool-kateeva-falls-victim-to-samsung-s-china-paranoia.

3.1 Fundamentals

Final-Good Production. We consider an open economy model with two countries $c \in \{A, B\}$ in continuous time. In each country, there is a representative final-good producer that combines the industrial goods into a final output, which is used for consumption and to pay the cross-border investment cost, whose price is the numeraire. The final-good production technology is the following CES composite of industrial goods:

$$\ln Y_c(t) = \int_0^1 \ln Q_{cj}(t)\, dj, \tag{3.1}$$

where $Q_{cj}(t)$ is the output of industry $j \in [0, 1]$ used in country c.

Industry Production. In each industry, two firms—one from each country—produce imperfectly substitutable varieties to meet the demand from both countries. Let $Q_{cj}(t)$ denote the output of industry j consumed in country c, and let $\{q_{cj}(t), q^*_{cj}(t)\}$ denote the amounts produced by the firm in country c operating in industry j to meet domestic and foreign demand, respectively—i.e., $q^*_{cj}(t)$ is exported. Without loss of generality, the industry output $Q_{Aj}(t)$ supplied to country A is then determined by the following CES technology:

$$Q_{Aj}(t) = \left(q_{Aj}(t)^{\alpha} + q^*_{Bj}(t)^{\alpha}\right)^{1/\alpha}. \tag{3.2}$$

$Q_{Bj}(t)$ is defined reciprocally. In this expression, $\alpha \in (0, 1]$ denotes the degree of substitution between the two varieties. As we shall see later, this parameter determines the distribution of production shares and thereby profits across firms in a given industry.

Each firm produces its variety with a linear technology using labor:

$$q_{cj}(t) = z_{cj}(t)\, l_{cj}(t), \tag{3.3}$$

where l_{cj} denotes the amount of labor used in production by firm (c, j), and z_{cj} denotes the firm's productivity level.[6] Accordingly, the marginal cost of production of firm (c, j) is given by w_t/z_{cj}. The firm with a higher productivity than its competitor has an edge over its rival in terms of marginal cost, which in equilibrium will allow this firm to capture a larger share of the industry revenue. Therefore, we will call the firm (c, j) the *leader* if $z_{cj} > z_{-cj}$ and the *follower* if $z_{cj} < z_{-cj}$. We say that firms in industry j are in *neck-and-neck* position if they produce with the same productivity.

The productivity with which the country c produces increases, proportionally with step size $\lambda > 1$, when there is a new business idea introduced by a domestic entrant (a new "startup"). When there is entry during the time interval Δt, the new startup replaces existing domestic incumbent, and

[6] To save on wording, we use the pair (c, j) to define that a firm is from country c operating in industry j.

the productivity level with which the new incumbent (c, j) operates becomes

$$z_{cj}(t + \Delta t) = \lambda z_{cj}(t).$$

Let us denote the number of technology rungs, i.e., productivity improvements, that took place in country c in industry j up to time t by $n_{cj}(t) \in \mathbb{N}$, and assume that the initial value of $z_{cj}(0)$ is normalized to 1. Then, the productivity level of firm (c, j) operating at time t is given by $z_{cj}(t) = \lambda^{n_{cj}(t)}$. Moreover, the relative productivity of (c, j) compared with its rival $(-c, j)$ is given by

$$\frac{z_{cj}(t)}{z_{-cj}(t)} = \frac{\lambda^{n_{cj}(t)}}{\lambda^{n_{-cj}(t)}} = \lambda^{n_{cj}(t) - n_{-cj}(t)} \equiv \lambda^{m_{cj}(t)},$$

where we denote the productivity difference or the technology gap between firm (c, j) and its rival $(-c, j)$ by m_{cj}.[7] We say that firm (c, j) is an m-step ahead leader (m-step behind follower) if $m_{cj} > 0$ ($m_{cj} < 0$). The technology gap is a sufficient statistic to describe firm-specific payoffs; therefore, we will drop the industry subscript j and use $m_c(t)$. We assume that in our economy there is a high upper bound $\bar{m}$ on the number of technology gaps, such that $|m| \leq \bar{m}$. This assumption ensures the finiteness of the state space. Finally, we denote the productivity gap at the industry level by $m_j(t) \in \{0, ..., \bar{m}\}$, for which $m_j(t) = |m_c(t)|$ holds true.

Startups and Foreign Investment. Incumbent firms remain in business until a domestic entrant (a new "startup") replaces them. In both countries, business ideas arrive to outside entrepreneurs at an exogenous Poisson arrival rate τ_c. An entrepreneur can immediately implement his or her idea to replace the domestic incumbent if that incumbent uses an inferior technology. But if an entrepreneur creates an idea that can potentially replace a domestic incumbent that is a leader in its industry, we assume that the entrepreneur needs outside financing to turn the business idea to a viable business venture.[8] In this event, there are three cases: (i) with $\bar{p}$, the entrepreneur finds financing domestically, (ii) if not, there may be foreign investment in the idea from the foreign (laggard) incumbent in that industry, (iii) if none of the first two options happens, there is no financing and the idea goes unimplemented.[9]

a business idea born in the country whose firm is leading in the particular industry, the laggard incumbent receives the chance to invest to that idea with probability $1 - \bar{p}$. The option arrives with an associated investment cost $\varepsilon \overset{iid}{\sim} [0, u_\varepsilon]$. If the cost is low enough and the firm chooses to invest in the foreign startup, the productivity gap between the new leader and the laggard incumbent opens up, as the foreign startup improves on the productivity of the leader that it replaces. However, although the laggard incumbent falls further behind, it starts benefiting from knowledge spillovers generated by the new foreign startup, in which it has invested. These spillovers arrive at an

[7] Notice that $m_{cj} = -m_{-cj}$.

[8] Conversely, we assume that business ideas that are to replace the laggard firm, which has inferior technology in the industry, can be funded by the entrepreneur's own means.

[9] Probability $\bar{p}$ is exogenously determined and is assumed to be common across countries and industries.

exogenous Poisson arrival rate δ. With probability ϕ, they improve the productivity of the laggard firm to the level at which the leader produces (quick catch-up), and with probability $1-\phi$, the improvement is only one step (slow catch-up).[10] As such, the two firms become neck-and-neck with probability ϕ, and the follower closes the gap by only one step with probability $1-\phi$. The laggard firm retains this position until it catches up with the leader or until a new foreign startup enters the business without receiving foreign investment. Finally, the investing firm earns a Δ share of the profits that the startup generates.

Figure 1 summarizes the possibilities associated with entry in a given industry in the leader country (the U.S. in this case). With $\bar{p}$, the idea is financed domestically. With the complementary probability, two cases may arise: (i) if the foreign investment cost is low enough (the equilibrium cutoff rule is presented below), the idea is funded by the rival incumbent from the foreign country, (ii) otherwise, the business idea is not implemented. In this setting, we will interpret u_ε—the upper bound of the domain of the random investment cost—as a policy parameter of the country that is leading in the industry. By increasing the upper bound u_ε, the government can decrease the possibility of the rival paying a relatively low investment cost to avoid potential spillovers to the rival in the future. However, this would come at the expense of reducing the probability of foreign investment and thus domestic entry, limiting potential productivity improvements.

Preferences. Finally, we describe the household side. Each country admits a representative household with the following log-utility:

$$U_c(t) = \int_t^\infty \exp\left(-\rho\left(\tilde{t}-t\right)\right) \ln C_c\left(\tilde{t}\right) d\tilde{t} \tag{3.4}$$

where $C_c(t)$ is consumption in country c, and $\rho > 0$ is the subjective rate of time preference. The budget constraint of the representative household is given as

$$r(t)A_c(t) + Lw(t) = P_c(t)C_c(t) + \dot{A}_c(t) + G_c(t), \tag{3.5}$$

where $r(t)$ is the worldwide return to asset holdings, L is the labor supplied inelastically by the household (normalized to unity in each country) and is mobile across countries, $w(t)$ is the common international wage rate, $P_c(t)$ is the aggregate price of consumption (equal to the numeraire), and $G_c(t)$ is the lump sum transfers distributed or taxes levied by the government. Finally, households own all firms in their country, and, under the assumption of full home bias, the asset-market clearing condition implies

$$A_{ct} = \int_0^1 V_{cj}(t)\, dj,$$

with $V_{cj}(t)$ denoting the value of the domestic incumbent firm industry j at time t.

[10] In the economy, there will be a basic level of knowledge spillover, which occurs at the Poisson arrival rate δ_0, generating the same probability of quick catch-up. However, we will assume that foreign investment unlocks spillovers at rate $\delta > \delta_0$.

3.2 Equilibrium

Production and Profits. As a result of the final-good technology, each representative final-good producer spends the same amount on each product j in their consumption basket. Therefore, the total expenditure from country c on the varieties from any industry j satisfies the budget constraint

$$p_{cj}(t)q_{cj}(t) + p^*_{-cj}(t)q^*_{-cj}(t) = P_c(t)Y_c(t) = Y_c(t) \quad \forall j \in [0,1]\,,$$

where the second equality holds because of the numeraire assumption. Here, $\{p_{cj}, q_{cj}\}$ denote the price and the quantity demanded of the domestic good, and $\{p^*_{-cj}, q^*_{-cj}\}$ denote the same values for the good imported from the other country (denoted by $-c$).[11]

The household chooses optimal variety bundle $\{q_{cj}, q^*_{-cj}\}$ subject to the budget constraint, and the resulting demand functions the two firms face are

$$q_{cj} = \frac{p_{cj}^{\frac{1}{\alpha-1}}}{p_{cj}^{\frac{\alpha}{\alpha-1}} + \left(p^*_{-cj}\right)^{\frac{\alpha}{\alpha-1}}} Y_c \quad \text{and} \quad q^*_{-cj} = \frac{\left(p^*_{-cj}\right)^{\frac{1}{\alpha-1}}}{p_{cj}^{\frac{\alpha}{\alpha-1}} + \left(p^*_{-cj}\right)^{\frac{\alpha}{\alpha-1}}} Y_c. \tag{3.6}$$

In our analysis, we abstract from trade frictions. Therefore, in equilibrium, $p_{cj} = p^*_{cj}$ holds for any industry—i.e., a firm charges the same price on goods it sells domestically or abroad (as shown below). As a result, $q^*_{cj} = q_{cj}\left(Y_{-c}/Y_c\right)$ holds in equilibrium.

The total industry revenue from selling to market (country) c is by definition Y_c. We denote the share of this revenue accruing to the domestic firm by $s_{cj} \equiv p_{cj}q_{cj}/Y_c$ and to the exporting foreign firm by $s^*_{-cj} \equiv p^*_{-cj}q^*_{-cj}/Y_c$. $s_{cj} + s^*_{-cj} = 1$ holds true. The resulting expressions for the shares are

$$s_{cj} = \frac{p_{cj}^{\frac{\alpha}{\alpha-1}}}{p_{cj}^{\frac{\alpha}{\alpha-1}} + \left(p^*_{-cj}\right)^{\frac{\alpha}{\alpha-1}}} \quad \text{and} \quad s^*_{-cj} = \frac{\left(p^*_{-cj}\right)^{\frac{\alpha}{\alpha-1}}}{p_{cj}^{\frac{\alpha}{\alpha-1}} + \left(p^*_{-cj}\right)^{\frac{\alpha}{\alpha-1}}}. \tag{3.7}$$

The optimal prices follow as

$$p_{cj} = \frac{1-\alpha s_{cj}}{\alpha\left(1-s_{cj}\right)}\frac{w(t)}{z_{cj}} \quad \text{and} \quad p^*_{-cj} = \frac{1-\alpha s^*_{-cj}}{\alpha\left(1-s^*_{-cj}\right)}\frac{w(t)}{z_{-cj}}. \tag{3.8}$$

Notice that the optimal pricing rule is an endogenous markup over the marginal cost of production. Finally, firms' profits follow as

$$\Pi_{cj} = \frac{s_{cj}\left(1-\alpha\right)}{1-\alpha s_{cj}} Y_c \equiv \pi_{cj} Y_c \quad \text{and} \quad \Pi^*_{-cj} = \frac{s^*_{-cj}\left(1-\alpha\right)}{1-\alpha s^*_{-cj}} Y_c \equiv \pi^*_{cj} Y_c. \tag{3.9}$$

As a consequence of unit-elastic demand at the industry level, equations (3.7)-(3.9) define firms'

[11] We drop the time notation unless it creates confusion.

revenue shares and thus profits from market c as an implicit function of their relative marginal costs and thus their relative productivities—i.e., $s_{cj} = g(m_{cj})$ and $s^*_{-cj} = g(-m_{cj})$. Therefore, $\Pi_{cj} = f(g(m_{cj}))$ and $\Pi^*_{-cj} = f(g(-m_{cj}))$. Moreover, notice that the revenue share of firm (c, j) when serving the domestic or foreign market is the same, thus $s_{cj} = s^*_{cj}$, as both markets differ only in terms of total household expenditure. The payoff-relevant state—the relative productivity levels of firms in the specific industry—is the same when producing for any market. Consequently, the total profits firm (c, j) generates from serving both markets is

$$\mathbf{\Pi}_{cj} = \Pi_{cj} + \Pi^*_{cj} = \pi_{cj} Y_c + \pi^*_{cj} Y_{-c} = \pi_{cj} (Y_c + Y_{-c}).$$

Notice that in equilibrium, given that there are no trade frictions, both countries produce the same amount of final good, i.e., $Y(t) \equiv Y_c(t) = Y_{-c}(t)$. (However, consumption levels could differ depending on the total income the country generates.) Therefore, we have $\mathbf{\Pi}_{cj} = 2\pi_{cj} Y$.

Dynamic Decisions and Firm Values. Let d_j denote the state of an industry with regards to flow of knowledge spillovers. The value $d_j = 1$ implies that the latest entrant in the country of the leading firm has received foreign financing, and that intra-industry spillovers are flowing at rate δ. This is the *high-spillover* state. $d_j = 0$ denotes the other case, in which spillovers occur only at the basic rate $\delta_0 < \delta$. This defines a *low-spillover* state. Then, we denote the stock market value of a firm whose productivity is $m_c \in \{-\bar{m}, ..., \bar{m}\}$ steps away from its competitor by V^d_{cm}.[12] Without loss of generality, we first define the value for a firm from A that is an m-step leader ($m_A > 0$) in a low-spillover industry ($d = 0$):

$$\begin{aligned} r(t)V^0_{Am}(t) - \dot{V}^0_{Am}(t) = \mathbf{\Pi}_{Am}(t) - \tau^0_{Am}(t)V^0_{Am}(t) + \tau_B \left[V^0_{Am-1}(t) - V^0_{Am}(t)\right] \\ + \delta_0\phi \left[V^0_{A0}(t) - V^0_{Am}(t)\right] + \delta_0(1-\phi) \left[V^0_{Am-1}(t) - V^0_{Am}(t)\right]. \end{aligned} \tag{3.10}$$

Let us dissect equation (3.10). The left-hand side is the flow value $\dot{V}(\cdot)$ denoting the change in value because of changes in aggregate variables (recall the definition of profits). The first item on the right-hand side is the total profits this firm earns from serving domestic and export markets. The second item is the result of domestic entry; when there is a domestic startup with necessary financing, the incumbent exits the business, destroying the value of the incumbent firm. The probability of a successful entrant depends on investment decision of the foreign firm and is an endogenous object defined by the function $\tau_m(t)$. The third term defines the change in value as a result of foreign entry, which happens at rate τ_B. The foreign entrant, which lags in productivity ($m_B < 0$), closes the productivity gap by one step, causing the leading firm lose its advantage by

[12] Notice that we drop the subscript j, as the identity of the industry does not matter once the pay-off relevant state variable, the productivity gap between the firms in that industry, and the rate of spillovers are known. Moreover, in a symmetric setting, we could also drop the country subscript c. However, we keep it, as differential government policies between two countries can render different values for two firms facing the same productivity gap with the rival.

one step. Finally, knowledge spillovers occur with Poisson arrival rate δ_0, which helps the follower close the productivity gap fully with probability ϕ—bringing the leader down to the neck-and-neck stage—or incrementally with probability $1-\phi$.

Next, we define the value for firm (A, m), an m-step follower ($m_A < 0$) in a low-spillover industry:

$$\begin{aligned} r(t)V^0_{Am}(t) - \dot{V}^0_{Am}(t) = \mathbf{\Pi}_{Am}(t) - \tau_A V^0_{Am}(t) + \delta_0\phi\left[V^0_{A0}(t) - V^0_{Am}(t)\right] \\ + \delta_0(1-\phi)\left[V^0_{Am+1}(t) - V^0_{Am}(t)\right] \\ + \tau_B\bar{p}\left[V^0_{Am-1}(t) - V^0_{Am}(t)\right] \\ + \tau_B\left(1-\bar{p}\right)\int_0^{u_\varepsilon} \max_{\kappa\in\{0,1\}} \kappa\left[V^1_{Am-1}(t) - V^0_{Am}(t) - \varepsilon Y(t)\right] d\varepsilon, \end{aligned} \tag{3.11}$$

where $Y(t)$ denotes final output. Again, the first two components on the right-hand side are profits and the effect of domestic entry. The third and fourth ones are the gain from spillovers, helping the follower reduce or fully close the productivity gap with the leader. The expression on the third line denotes the effect of foreign entry funded by domestic firms, which happens with probability $\bar{p}$. In that case, the productivity gap opens up one more step, and the follower firm's position deteriorates to $m-1$.

The last line in equation (3.11) describes what happens when the firm gets the chance to invest in the foreign startup, which occurs with the complementary probability $1-\bar{p}$. An opportunity to undertake a foreign investment comes with a random investment cost $\varepsilon \overset{iid}{\sim} [0, u_\varepsilon]$ (the total investment cost is assumed to scale with aggregate output since firm values grow over time). The firm decides to pay this cost ($\kappa = 1$) only if it is less than the incremental gain in firm value from this investment. This gain reflects the benefit of transitioning to a high-spillover state—with spillovers from the funded foreign startup occurring at rate $\delta > \delta_0$ and additional profits received—although successful foreign entry due to cross-border investment still causes the productivity gap to increase one more step. If the firm forgoes the chance to invest, its state remains the same, as the foreign business idea is not implemented due to a lack of funding.

With a constant gain from cross-border investment and a linear cost of so doing, the optimal decision follows a cutoff rule. The firm optimally invests in the foreign startup when the random cost ε is less than the cutoff value

$$\bar{\varepsilon}^0(m,t) = \frac{V^1_{Am-1}(t) - V^0_{Am}(t)}{Y(t)}.$$

The cutoff depends on the productivity (dis)advantage, which determines the magnitude of the value increase from the investment. Consequently, the optimal decision rule is

$$\kappa^0(m) = \begin{cases} 1 & if \quad \varepsilon < \bar{\varepsilon}^0(m) \\ 0 & if \quad \varepsilon > \bar{\varepsilon}^0(m) \end{cases}. \tag{3.12}$$

We now turn to the value functions of firms in high-spillover state. Starting with an m-step ahead leader, we have

$$r(t)V^1_{Am}(t) - \dot{V}^1_{Am}(t) = (1-\Delta)\mathbf{\Pi}_{Am}(t) - \tau^1_{Am}(t)V^1_{Am}(t) + \tau_B\left[V^1_{Am-1}(t) - V^1_{Am}(t)\right]$$
$$+ \delta\phi\left[V^0_{A0}(t) - V^1_{Am}(t)\right] + \delta(1-\phi)\left[V^1_{Am-1}(t) - V^1_{Am}(t)\right]. \tag{3.13}$$

This value function is similar to the value of a leader in state $d_j = 0$, except that the firm sends a Δ fraction of its profits. The value of an m-step behind follower is again similarly defined as in the low-spillover state:

$$\begin{aligned} r(t)V^1_{Am}(t) - \dot{V}^1_{Am}(t) = {} & \mathbf{\Pi}_{Am}(t) + \Delta\mathbf{\Pi}_{Bm}(t) - \tau_A V^1_{Am}(t) \\ & + \delta\phi\left[V^0_{A0}(t) - V^1_{Am}(t)\right] + \delta(1-\phi)\left[V^1_{Am+1}(t) - V^1_{Am}(t)\right] \\ & + \tau_B\bar{p}\left[V^0_{Am-1}(t) - V^1_{Am}(t)\right] \\ & + \tau_B(1-\bar{p})\int_0^{u_\varepsilon} \max_{\kappa\in\{0,1\}} \kappa\left[V^1_{Am-1}(t) - V^1_{Am}(t) - \varepsilon Y(t)\right] d\varepsilon, \end{aligned} \tag{3.14}$$

Notice that this laggard receives the Δ fraction of the profits that the new industry leader generates, as the leader firm emerged after the investment from the follower. Moreover, the follower in this high-spillover state could still optimally decide to re-invest into a new potential idea to get a claim on the larger profits the next emerging startup would generate. The cutoff rule is defined reciprocally as in equation 12:

$$\kappa^1(m) = \begin{cases} 1 & if \quad \varepsilon < \bar{\varepsilon}^1(m) \\ 0 & if \quad \varepsilon > \bar{\varepsilon}^1(m) \end{cases}, \tag{3.15}$$

with the cutoff value given as

$$\bar{\varepsilon}^1(m,t) = \frac{V^1_{Am-1}(t) - V^1_{Am}(t)}{Y(t)}.$$

Finally, the value of a firm in neck-and-neck stage is given by

$$r(t)V^0_{A0}(t) - \dot{V}^0_{A0}(t) = \mathbf{\Pi}_{A0}(t) - \tau_A V^0_{A0}(t) + \tau_B\left[V^0_{A-1}(t) - V^0_{A0}(t)\right]. \tag{3.16}$$

Notice that spillovers are not relevant for a firm that is in neck-and-neck stage. As a result, it follows that $V^1_{c0} = V^0_{c0}$.

To render the dynamic problem stationary, we will use normalized value functions. We define

$v(t) = V(t)/Y(t)$. Then, the normalized flow value of a generic firm is defined as

$$\frac{r(t)V(t) - \dot{V}(t)}{Y(t)} = r(t)v(t) - (\dot{v}(t) + g(t)v(t)) = (r(t) - g(t))\, v(t) - \dot{v}(t), \tag{3.17}$$

where $g(t) = \dot{Y}(t)/Y(t)$ denotes the growth rate of aggregate output. (Notice that in the balanced growth path, this growth rate also corresponds to the growth rate of consumption in each country.) Then, the normalized value function of a leader firm in a low-spillover state becomes, for example:

$$\begin{aligned}(r(t) - g(t))\, v^0_{Am}(t) - \dot{v}^0_{Am}(t) = 2\pi_{Am}(t) - \tau^0_{Am}(t)v^0_{Am}(t) + \tau_B \left[v^0_{Am-1}(t) - v^0_{Am}(t)\right] \\ + \delta_0\phi \left[v^0_{A0}(t) - v^0_{Am}(t)\right] + \delta_0(1-\phi) \left[v^0_{Am+1}(t) - v^0_{Am}(t)\right]. \end{aligned} \tag{3.18}$$

Other normalized value functions are defined accordingly.

Balanced Growth Path. A balanced growth path (BGP) equilibrium is defined as an equilibrium where all aggregate variables and value functions grow at the same rate g in both counties. Looking first at the value of a leader firm in a low-spillover state, we obtain

$$\begin{aligned}(r - g)\, v^0_{Am} = 2\pi_{Am} - \tau^0_{Am}v^0_{Am} + \tau_B \left[v^0_{Am-1} - v^0_{Am}\right] \\ + \delta_0\phi \left[v^0_{A0} - v^0_{Am}\right] + \delta_0(1-\phi) \left[v^0_{Am+1} - v^0_{Am}\right]. \end{aligned} \tag{3.19}$$

Notice that $\dot{v}(t) = 0$, as the normalized functions become stationary in BGP. Again, the other value functions are defined accordingly.

The cost cutoffs for investment decisions remain constant over time in BGP. In particular, the cutoff for an m-step follower in low-spillover state becomes

$$\bar{\varepsilon}^0(m) = v^1_{Am-1} - v^0_{Am},$$

and the value of the firm simplifies to

$$\begin{aligned}(r - g)\, v^0_{Am} &= 2\pi_{Am} - \tau_A v^0_{Am} + \delta_0\phi \left[v^0_{A0} - v^0_{Am}\right] + \delta(1-\phi) \left[v^0_{Am+1} - v^0_{Am}\right] \\ &\quad + \tau_B\bar{p} \left[v^0_{Am-1} - v^0_{Am}\right] \\ &\quad + \tau_B\,(1-\bar{p})\, \Pr\left[\varepsilon < \bar{\varepsilon}^0(m)\right] \times \left\{\left[v^1_{Am-1} - v^0_{Am}\right] - \mathbb{E}\left[\varepsilon | \varepsilon < \bar{\varepsilon}^0(m)\right]\right\} \\ &= 2\pi_{Am} - \tau_A v^0_{Am} + \delta_0\phi \left[v^0_{A0} - v^0_{Am}\right] + \delta(1-\phi) \left[v^0_{Am+1} - v^0_{Am}\right] \\ &\quad + \tau_B\bar{p} \left[v^0_{Am-1} - v^0_{Am}\right] + \tau_B\,(1-\bar{p})\, \frac{\left[v^1_{Am-1} - v^0_{Am}\right]^2}{u_\varepsilon}. \end{aligned} \tag{3.20}$$

Notice that a higher maximum value for the investment cost (u_ε) decreases the probability that

the firm receives a low enough cost, thereby depressing the last component and thus the value of the firm. The expression for the m-step follower in high-spillover state is defined correspondingly.

3.3 Model Discussion

The model presents a rich setting that captures the essence of foreign corporate venture investment highlighted in the empirical section. A venture investment by a foreign corporation in the model benefits the investor in both pecuniary (additional profits) and non-pecuniary (spillovers) ways. Reflecting on the findings presented in Section 5.2.2, investing firms increase their patenting (measured by a higher δ) after an investment.

The model also provides a useful framework to investigate the determinants of the foreign corporate venture investment, discussed in Section 5.2.1. A key pillar of the model is the technology gaps between firms, which evolve endogenously. We can analyze how investment decisions of foreign entities change depending on where they stand in the technological race relative to their competitors. The exact nature of this relationship is a quantitative question that we illustrate numerically below.

Finally, the model allows us to reflect on the relationship between the basicness of a patent class and the presence of foreign corporate venture investment. In the numerical examples below, we will define more basic classes as those with a lower baseline level of spillovers, building on the idea that it is harder to learn from the advanced basic research done by the frontier firms.

In addition to the positive analysis, we use this framework for policy analysis. In particular, we will analyze whether the United States would benefit from allowing a higher or lower level of foreign corporate venture investment. The policy parameter that is determined by the domestic policymakers is the range of the investment cost that the foreign entities face. We will discuss the effect of the changes in this parameter at the end of the numerical analysis below.

4 Numerical Example

To illustrate the key implications of our framework, we now present a numerical example. Our goal is not to provide a detailed calibration of the model economy, but to highlight its qualitative implications for cross-border financing and optimal policy under plausible parameter values.

4.1 Parameters

In the numerical exercise, we assume countries are symmetric except for their entry rates. As such, we have a set of ten parameters to be determined, out of which four $(\lambda, \alpha, \bar{p}, u_\varepsilon)$ are determined internally. Given our focus on foreign corporate venture investments and subsequent innovative activity of firms, we discipline most parameters using statistics from our sample used in the empirical

section and the U.S. Patent and Trademark Office (USPTO) patent database. The parameter values are summarized in Table 1.

External Parameters. We set the subjective rate of time preference of the household (ρ) in a way that the real rate of return on risk-free assets r mimics the average long-run U.S. interest rate of around 6 percent (Cooley and Prescott, 1995; Akcigit et al., 2016). The household has a logarithmic utility function, and, under the assumption that assets are owned domestically, the Euler equation resulting from her optimization problem implies $\rho = r - g$. With the calibrated growth rate g (see Table 2), $\rho = 0.03$ implies an interest rate consistent with the data.

We pick the idea generation intensities (τ_c) to reflect the ratio of the total number of (citation-weighted) patents registered by foreign and U.S. entities in the USPTO database over the period 1976–2015. Over this period, 63 percent of the weighted patents are registered by U.S. entities.[13]

Next, we need to determine the spillover rates before and after the investment event in the model (δ_0, δ). To accomplish that, we rely on information that we obtain from our empirical exercises regarding the increase in the patenting activity of investing firms (the treated group in our exercises) upon investment. Specifically, the average number of annual patent applications submitted by a foreign country in a given patent class in which it invests in the five years before the investment event is 50.6 for the treated group.[14] The increase in the five years after the investment (relative to the increase in the control group) is 4.7. We thus use 50 and 55 as the reference values and, accordingly, assume a 10 percent increase in the spillover rate after the investment (δ) relative to the baseline spillover rate (δ_0). Pinning down the level of the baseline spillover rate—equivalently, the scale of these parameters—is harder, as measuring international spillovers empirically is notoriously difficult. We set $\delta_0 = 0.5$ (thus $\delta = 0.55$) in line with the range of estimates found in prominent work on international R&D and knowledge spillovers.[15] This value for the baseline spillover rate implies that new technologies arrive every two years (δ_0^{-1}). We will present a sensitivity analysis of our results to faster or lower arrival of new technologies.

The share of drastic innovations in spillovers (ϕ), which determines the rate of quick catch-up, is set to reflect the share of foreign patents whose citation count is in the top five percent of the citation distribution across all patents. This ratio gives the rate with which foreign firms produce

[13] We normalize the total number of ideas generated in a unit time interval to 1.

[14] In Table 4, we report "annual patent applications in class by foreign country" as 13.04. The reason why the numbers quoted here are much larger than the averages in Table 4 is because the places where foreign CVCs invest are non-random. That is, they tend to invest in places where they are already patenting more than average.

[15] Most relevant for our purposes, Peri (2005) estimates that the elasticity of patenting in a region to foreign R&D varies between 50-80 percent of its elasticity to domestic patenting. In addition, he estimates that about 50 percent of knowledge originating from most innovative regions (the technology frontier) reach beyond domestic borders, with close to 40 percent reaching farthest destinations (beyond 10,000 km). Our choice for δ_0 is in line with these findings. Another branch in this literature measures R&D spillovers estimating the elasticity of TFP growth to foreign R&D. In a seminal paper analyzing a set of 22 industrialized economies, Coe and Helpman (1995) find that the elasticity of TFP to foreign R&D is between 0.25 and 1.5 times its elasticity to domestic R&D. Using a different estimation method, Keller (2002) argues for a much stronger contribution of foreign R&D to domestic TFP. Finally, using a cost function estimation approach for OECD countries, Nadiri and Kim (1996) estimate that the gain from R&D in terms of cost reduction abroad is between 40 to 65 percent of the domestic gain. Again, our choice of δ_0, which can also be translated into the gain from foreign innovation relative to the source, falls to the middle of this range.

highly influential patents. We assume that the VC-backed startup and the investor share the profits generated by the startup equally. (Unfortunately, we do not have a convincing empirical measure of the profit share, so assume an equal split in the baseline numerical example and provide a sensitivity analysis around this value.) Finally, we allow for a maximum gap of 30 such that $\bar{m} = 30$. This is a conveniently high limit, allowing leader firms maintain a non-trivial technological gap with the followers. This property ensures a smooth distribution of firms across technology gaps.[16]

Internal Parameters and Moments. We determine the rest of the parameters using a simulated method of moments (SMM) approach. These parameters do not correspond to a directly observable counterpart in the data. However, they determine certain moments in the model, whose empirical counterparts we can back up from the data. As such, the calibration based on SMM pins down these parameters by minimizing the difference between a set of model–based moments—which are informative about the parameters to be calibrated—and their empirical counterparts (we detail the set of calibrated moments below). The procedure minimizes the following objective function, which maps the set of four parameters to the distance between the model–based moments and the empirical targets (see Acemoglu et al., 2018):

$$\sum_{k=1}^{N} \frac{|\text{model}(k) - \text{data}(k)|}{\frac{1}{2}|\text{model}(k)| + \frac{1}{2}|\text{data}(k)|},$$

where k denotes each moments and $N = 4$ is the number of targets. The bottom panel of Table 1 presents the parameters that jointly minimize this objective function.

The four targets we include in the internal calibration are (i) the average growth rate of the U.S. real GDP (in 2012 dollars), (ii) the average ratio of non-financial corporate profits to U.S. GDP, (iii) the share of VC-backed firms among U.S. firms that have been issued a patent, and (iv) the share of patenting firms receiving venture financing that had at least one foreign investor. These targets inform the calibration as follows. In this model, as is the case in standard quality ladder models of endogenous growth, the growth rate is determined by the arrival rate of innovations and the step size. Given other parameters, the first target helps determine the step size. Note the calibrated value 1.056 is in the ballpark of estimates found in the literature (Acemoglu and Akcigit, 2012). The profit share of GDP disciplines the CES parameter, which determines the substitutability between the two varieties in the industry, and thus, the profits firms can charge, given their technological advancement relative to their rival. The final two targets are most informative about the remaining parameters u_ε and $\bar{p}$, as u_ε shapes foreign VC investment in the model—taken to be symmetric for both countries in the calibrated model—and $\bar{p}$ determines the probability of receiving domestic financing.[17]

We discipline the four empirical targets in Table 2 as follows. The first two are computed from the BEA database and are averages over the sample period. Of all U.S. patent awards with a U.S.

[16] For comparison, Akcigit et al. (2018) takes $\bar{m} = 16$ in their baseline quantitative exercises.

[17] See Section 4.3 for how we model the change in the cost of foreign VC investment as a result of country-specific policy.

assignee in the sample, 25.3 percent are assigned to firms that raise venture financing at some point between 1962 and 2017, which we use as the third moment. For the final one, of all U.S. firms that received venture financing from 1962 to 2017 and have at least one patent awarded between 1976 and the end of 2017, 63.1 percent received at least one financing from a foreign venture group. The calibrated model hits these moments exactly, as summarized in Table 2.

4.2 Taking Stock

Now we turn to the illustration of the key implications of the model. First, the model captures that the patenting intensity of foreign firms rises after VC investment, because the rate of spillover arrival increases with investment ($\delta > \delta_0$). We will corroborate this insight in Section 5.2.2.

Figure 2a shows the investment decisions of firms from country B—which denotes the foreign country—in the balanced growth path. The red line represents the probability for laggards in the low-spillover state and the blue dashed line pertains to the laggards in the high-spillover state (leaders do not engage in VC activity). The figure reveals that for a laggard firm, the cross-border investment probability increases with the technological distance to the frontier. This result conforms with the empirical findings to be discussed in Section 5—countries make VC investments more in sectors where they have less knowledge relative to the United States. That lower relative knowledge is captured by wider technology gaps in our model. As foreign firms fall too far behind, their willingness to invest in the domestic startups reaches the maximum. The investment probability quickly declines as the gap between foreign and domestic firms diminishes and reaches zero when they are close to neck-and-neck.

Next, we illustrate the relationship between basicness of a sector and the foreign corporate venture investment probability. To that end, we consider an economy that is different from the calibrated one only in a lower baseline spillover rate ($\delta_0' < \delta_0$). The lower intensity of the baseline spillover rate reflects the idea that it is more difficult to learn from the advanced basic research conducted at the frontier. Figure 2b exhibits the excess investment probability in that hypothetical economy relative to the baseline. The model implies that the probability of investment is higher in the economy with more basic sectors, especially for laggards that are relatively closer to the frontier, in accordance with the empirical findings. For laggards that are farther away, the investment intensity is slightly lower, although those firms invest almost at the maximum rate as in the calibrated version. We will report evidence consistent with these suggestions in Section 5.2.2.

In sum, the numerical analysis based on a calibrated version of the model highlights the ability of the model to replicate key empirical relationships documented below. Now, we turn to the welfare implications of policies.

4.3 The Social Planner's Problem, Policy Analysis, and Welfare

In this section, we discuss how the welfare of the representative U.S. consumer responds to changes in the rate of foreign corporate venture penetration. In the numerical example above, we assumed a symmetric structure in the cost of VC investment abroad for both countries. Now, we assume that the United States has a policy tool to affect the upper bound of the cost distribution, from which the foreign investors draw their cost. Precisely,

$$u_{\varepsilon}^{B} = (1+\sigma)u_{\varepsilon},$$

where the σ denotes the policy parameter, with which the United States can affect the foreign investors' cost parameter proportionally. In the calibrated economy, σ is equal to zero.

In addition, we assume that foreign corporate venture capital investment poses an economic security threat to the recipient country that is increasing in the number of foreign investors.[18] We model this security cost in terms of domestic output using the following functional form:

$$C_{c}^{sec}\left(\Omega_{-c1}\right) = \chi_0 \Omega_{-c1}^{2} Y_c,$$

where Ω_{-c1} denotes the measure of foreign firms that have investments in domestic firms. Notice that this aggregate cost is an externality of firm decisions, which firms do not take into account in the decentralized equilibrium.

In the following numerical exercise, we set the scale parameter $\chi_0 = 2.80$. It is not straightforward to discipline the cost of the security threat posed by foreign firms that learn about the technology of the U.S. firms. However, historical records provide some idea about how much of national income policy makers would be willing to forgo to protect against a large threat from an adversary. In particular, we set χ_0 as to match the post-war spending of the U.S. military on the research and development of nuclear bombs to deter the use of such arms by other countries. Detailed estimates from Schwartz (1998) suggest that the United States spent about 1.6 percent of its GDP in the five decades after the WWII on the development and deployment of nuclear armaments. We present additional results based on a broader cost measure including other costs such as maintenance, which take the cost to about 2.3 percent of GDP.[19] A different set of estimates with a similar magnitude is that of the cost that trade secret theft (including military, civilian, and dual use technologies) represents to the U.S. economy, which range from 1 to 3 percent of GDP (Passman et al., 2014).

Figure 3a shows the change in consumption-equivalent welfare as σ moves from -0.70 to 0.70. As the figure shows, the U.S. consumers benefit from a lower σ—i.e., from higher penetration by foreign investors (Figure 3b). The optimal σ^* suggests a 52 percent reduction in the barriers to foreign investment. This implication stems mainly from the higher growth rate achieved in the economy

[18] These threats are acknowledged even by those outside the defense community: see, for instance, the comments of the National Venture Capital Association, 2019.

[19] See Table 1 in Schwartz (1998).

(Figure 3c) as a result of a higher rate of idea implementation supported by foreign investment. However, decreasing σ further to encourage more corporate VC investments is suboptimal, because the security cost rises steeply, as shown in Figure 3d.

Alternatively, when the security is assumed to be higher—2.3 percent of GDP, implying $\chi_0 = 3.85$—the optimal policy is to impose higher barriers to foreign corporate venture investment (Figure 4a). We contend that this fraction of GDP serves as a quite high bar for the security threat that may be posed by foreign firms learning about the U.S. technology and using it to develop potentially harmful technologies. Therefore, the results suggest that, for most estimates, the policy prescription appears to be to attract more foreign investment into U.S. firms.

Sensitivity. Finally, we discuss briefly the sensitivity of our main policy results to some of the externally calibrated parameters. As mentioned in Section 4.1, our data do not allow us to directly pin down the baseline spillover rate (δ_0) and the share of profits a VC investor retains from the startup in which it invests (Δ). To assess the sensitivity of our results to these parameters, we consider a higher and lower value for each of these parameters and rerun the internal calibration exercise keeping other externally calibrated parameters fixed.[20] In each exercise, we also reset χ_0 to a value that keeps the security-cost-to-GDP ratio in the model at the benchmark empirical value, so that we can compare the results in these alternative economies to our benchmark findings shown in Figure 3. Finally, we calculate the optimal policy (σ^*) in each alternative economy.

Table 3 shows the optimal government policy (σ^*) in each of the four alternative economies. For both δ_0 and Δ, we experiment with values $\{0.30, 0.70\}$ (recall that the calibrated value for both parameters is 0.50). The results suggest that the optimal level of σ varies sharply in the alternative economies, especially when the spillovers are happening at a high rate. However, our main finding that the optimal policy reduces the barriers to foreign investment remains intact in all the alternative economies we consider. Therefore, we conclude that our benchmark finding is robust to a wide range of values for the specific parameters and the alternative calibrations considered here.

5 Empirical Analysis

In this section, we describe our empirical analysis.

5.1 Data

We begin by describing the data that we use for our analysis.

[20] In the exercises where we change δ_0, we keep the proportional increase in the spillover rate after investment from δ_0 to δ unchanged at the benchmark level dictated by our empirical findings. In all exercises, the alternative calibration hits the targets listed in Table 2 almost exactly, if not perfectly.

5.1.1 Sources

We obtain data on VC investments from the Refinitiv VentureXpert database (formerly called Thomson Reuters VentureXpert and Venture Economics). VentureXpert, along with CB Insights' VentureSource (formerly VentureOne), are the venture capital databases with the most extensive historical data. We use VentureXpert because it starts earlier (1962 vs. 1994) and has been found to be more comprehensive in terms of investment coverage, which is important for our purposes.[21] VentureXpert records detailed information about the dates of venture financing rounds, the VC firms and companies involved, the amounts invested by each party, and the ultimate company outcome.

To examine whether there is evidence of international technology spillovers stemming from cross-border investments, we need to identify investments in U.S. startups by foreign entities, particularly corporations. While VentureXpert does provide information on both headquarters location and corporate affiliation status of each venture group, this information is somewhat unreliable. At times, a VC firm that appears to be independent is really an investment arm of a corporation, which may be based in a different country. Therefore, using a number of sources, we compiled a list of all known CVC firms, along with the countries that their ultimate parents are located in.[22] Using this list, we correct the corporate affiliation status and headquarters location of mis-categorized VC firms in the VentureXpert data. Our results remain broadly similar, however, using the raw data.

We measure knowledge flows across countries using patent data from the USPTO. We focus on U.S. patent filings, rather than looking in filings in the home countries of the various corporate venture investors for three reasons. First, patent protection in a given nation is conditional on filing for patents in that nation: given the size of the U.S. market, most important inventions will be filed here (see Lanjouw et al. (1998) for a discussion). Second, patent policy differs substantially across nations: both the extent of review and typical patent breadth differ dramatically. By just focusing on U.S. awards, we run less danger of comparing quite heterogenous awards. Finally, patent policy and practice has been quite dynamic in many nations, such as China and Japan, introducing inter-temporal differences. Policy in the U.S. has been more stable, at least since the years after the creation of the Court of Appeals for the Federal Circuit in 1982.

We use all utility patents granted from 1976 to 2017 in the USPTO data.[23] Among other things,

[21] Maats et al. (2011) and Kaplan et al. (2002) compare VentureXpert against samples of financing rounds obtained from original sources and find reasonably good coverage, albeit with concerns about valuation and outcome data (neither of which will be used here).

[22] Sources used include lists of CVCs compiled by Global Corporate Venturing, CB Insights, and Crunchbase. We also manually check (using media reports and filings with the U.S. Securities and Exchange Commission) for any corporate affiliations among seemingly independent foreign investors in U.S. startups. For example, we identify "Blue Pool Capital" as being affiliated with Alibaba due to the fact that it invests the personal wealth of multiple Alibaba founders (e.g., Jack Ma and Joe Tsai).

[23] In addition to utility patents, there are several other minor patent categories, such as design, reissue, and plant patents. Following the literature, we focus only on utility patents, which represent approximately 90% of all awards (Jaffe and Trajtenberg (2002)).

the data provide information on the dates a patent was applied for and ultimately granted, its detailed technology class, the company it was originally assigned to (i.e., its "assignee"), and the location of the company it was originally assigned to. We match the patent data with VentureXpert using standardized company and location names along with the company's founding date and the date of the assignee's first patent application. The details of the matching procedure are provided in the Appendix. Using this matching procedure, we find that approximately 29% of VC-backed companies in VentureXpert are also patent assignees in the USPTO data. Approximately 41% of VC financing rounds in VentureXpert are associated with companies that are also patent assignees in the USPTO data.

5.1.2 Key Variables and Summary Statistics

Here we describe a few key variables used in our analysis. Table 4 provides summary statistics for these variables.

Patents

Most of our analysis is at the country×technology-class×year level. We define a patent's country based on the country of its assignee, as indicated in the patent award. Patents with assignees from multiple countries are attributed equally to all of the countries of the assignees. We define a patent's class based both on its primary (three-digit) U.S. Patent Classification (USPC) and its primary (four-digit) Cooperative Patent Classification (CPC) code. The U.S. switched to classifying patents using the CPC scheme at the start of 2015. For patents granted before 2015, we obtain a CPC classification from USPTO's back-filled classifications (using the CPC Master Classification File for U.S. Patent Grants). For patents granted after 2015, we obtain a USPC classification through our own imputation procedure, based on the modal USPC class associated with each CPC class historically.

Finally, we follow the economics of innovation literature and define a patent's year based on the year it was applied for. (A patent's application date is closer to the date the underlying innovation was actually discovered: there can be a significant gap between the two dates.) It should be noted that, while we focus on patent application dates, all of our patent-based measures are based only on eventually-granted patents, as application data for non-granted patents are only available starting in 2001.

Patent citations to U.S. startups

Patent citations are important in patent filings since they serve as "property markers" delineating the scope of the granted claims. Hall et al. (2005) illustrate that citations are a good measure of innovation quality and economic importance. Specifically, they find that an extra citation per

patent boosts a firm's market value by 3%. Moreover, Kogan et al. (2017) show that the stock market reaction to a patent approval is a strong predictor of the number of future citations a patent receives. We use patent citations as a way of measuring knowledge flows from U.S. startups to foreign entities. Citations are measured through the end of 2017.[24]

Investment in U.S. startups

One of the key variables in our analysis is CVC investments from a foreign country, f, into U.S. startups innovating in a technology class, c, in a given year, t. We construct several measures to capture this. First, we construct binary investment variables. In this case, we define a country f to have invested in a technology class c in a given year t if a corporation based in f invested in a U.S. startup that had any (or a majority or mode) of its patent applications in class c as of the time of investment in year t.

We also construct continuous investment variables as well, which represent the amount that corporations based in country f invested in a technology class c in a given year t. However, for this measure, in cases where a startup patents across different classes, we need to allocate different portions of an investment to different technology classes. In such cases, we allocate a given investment to different classes based on how frequently the startup applied for patents in each class prior to year t. For example, suppose that 20% of the patents a startup applied for prior to year t were in class A, 30% were in class B, and 50% were in class C. If a CVC group invested \$100 million in that startup in year t, we would define it as having invested \$20 million in class A, \$30 million in class B, and \$50 million in class C. We then sum up all such investments by corporations in the same country and year to construct our continuous measure of investment.

Basicness of a technology class

In order to distinguish basic innovation fields from applied ones, we construct a measure of how fundamental each technology class is. We assume that patents that cite academic publications rely on scientific discoveries inside academia and thus are more likely to contain complex and fundamental innovations than patents that do not cite academic articles. The data on the citations to academic publications come from Marx and Fuegi (2020) and include patents filed between 1926 and 2018.

For each technology class and year, we define a measure of the class's "basicness" as the number of backward citations to academic publications in the annual patent applications belonging to the class. For each year, we then divide the classes into two groups: patent classes whose number of

[24]The use of patent data may be questioned in domains where national security concerns are the highest, either because firms are reluctant to make disclosures or because they involve technologies where patents have traditionally been more difficult to obtain (e.g., software). It should be noted, however that many technologies have civilian and military applications, which may provide a motivation for patenting, and that software patenting has become ubiquitous in recent decades (Chattergoon and Kerr, 2022).

backward academic citations are above and below the year-specific median. We call the former "High Basicness" patent classes and the latter "Low Basicness" patent classes.

Knowledge of a foreign country relative to the U.S.

Another variable we are interested in is the knowledge of foreign country f relative to the U.S. in a given technology class c and year t. We define this variable as:

$$RelativeKnowledge_{f,c,t} = \frac{CumulativePatents_{f,c,t}}{CumulativePatents_{f,c,t} + CumulativePatents_{us,c,t}},$$

where $CumulativePatents_{f,c,t}$ represents the total number of (eventually-granted) patent applications in class c that entities in country f applied for prior to year t; and $CumulativePatents_{us,c,t}$ represents the same for the U.S.

5.1.3 Trends in foreign investment in U.S. startups

Our merged sample includes 524 corporations with affiliated VC units. Of these, 344 (66%) are non-U.S. based and are domiciled in 32 distinct foreign countries. Most of our analysis focuses on these 344 foreign corporate VC investors. These firms invested in 3,560 different U.S. startups during our sample period, among which 1,842 startups were granted at least one patent. The top six home countries of the foreign corporations that invested in U.S. startups from 1976 to 2015 by capital invested are Japan (24.0%), Germany (11.5%), Switzerland (9.4%), United Kingdom (6.9%), France (6.9%), and Singapore (6.7%).[25]

To put our analysis in context, we start by documenting time trends in cross-border CVC investment in the U.S. Figure 5, Panel A shows the share of aggregate VC investment in the U.S. made by foreign CVCs over time. Over the past several decades, foreign corporations have substantially increased their presence in venture capital markets. The share of VC investments in the U.S. made by foreign corporations increased from approximately 0.18% in 1979 to 3.78% by 2015.[26] The last two panels show that this increase was due to an increase in both CVC investment more generally during that time period (Panel B) and the share of CVC investment made by foreign corporations (Panel C).

[25] If we compile a similar list of the top foreign countries from 1976 to 2017 (that is, adding two additional years), China rises to second place with 10.7%.

[26] It might be argued that the amount of financing provided by foreign corporate venture capitalists is very modest compared to the venture pool overall, raising questions about the credibility of our assumption that such foreign CVC investment may be a way to ease capital constraints engendered by a lack of domestic funding. Two additional considerations are that (a) the amount of foreign corporate funding may be unevenly distributed, and represent a much larger share in certain industries such as computer hardware (as the motivating example in Section 2 suggests), and (b) investments by foreign independent venture capitalists, while not included in this tabulation, may also be associated with knowledge transfers abroad.

5.2 Results

5.2.1 Determinants of cross-border startup investments

We begin by exploring the determinants of cross-border startup investments. In particular, we investigate whether foreign entities tend to make these investments in technological areas where their country is behind relative to the U.S., or in areas where their country already has expertise relative to the U.S. To answer this question, we estimate equations of the form:

$$Investment_{fct} = \alpha_0 + \beta RelativeKnowledge_{fct} + \gamma_f + \eta_t + \varepsilon_{fct}, \tag{5.1}$$

where $Investment_{fct}$ is a measure of country f's investments in U.S. startups specializing in class c during year t; $RelativeKnowlege_{fct}$ is defined in Section 5.1.2 and represents the knowledge of country f relative to the U.S. in class c as of year t; γ_f represents country fixed effects; and η_t represents year fixed effects.

The results are shown in Table 5. In columns 1–2, we measure investment simply as an indicator variable equal to one if, during year t, corporations in country f made any investments in U.S. startups that had patent applications in class c. We find that as a country increases its knowledge of a technology class relative to the U.S., it also becomes less likely to invest in a U.S. startup innovating in that technology class.

In columns 3–4, we measure investment continuously, as the share of country f's investments in U.S. startups during year t that were allocated to patent class c. We find qualitatively similar results using this continuous measure as well.

Overall, these results show that foreign countries tend to invest in U.S. startups that specialize in technological areas where they are behind the U.S. While the findings are correlational in nature, they are consistent with a potential learning motive for cross-border startup investments. In the next section, we more directly examine whether there is evidence that foreign entities learn from investments in U.S. startups.

5.2.2 Do foreign entities learn from investments in U.S. startups?

If foreign entities learn from investing in U.S. startups, we might expect to see such learning reflected in the nature of their own innovative activities subsequent to investing. Therefore, we next look at how a foreign country's innovation in a technology class evolves after entities there invest in a U.S. startup specializing in that technology. Of course, it is difficult to estimate the effect of a country's cross-border startup investments on its own innovation, as cross-border startup investments are endogenous. Indeed, technology classes may experience shocks that lead foreign entities to try to innovate in those classes and also to invest in U.S. startups innovating in those classes. Thus, even absent any learning, there may be a positive correlation between a country's cross-border

investments in a technology class and its own innovations in that class. This is a manifestation of the Manski (1993) reflection problem.

To address such endogeneity concerns as effectively as possible, we use a difference-in-differences approach. Specifically, we focus on the period surrounding a country's first investment in a U.S. startup specializing in a particular technology class. We then compare changes in the country's innovative activity in that "treated" technology class to changes in the same country's innovative activity in a similar "control" technology class, in which it never invested. We match treated classes to control classes based on two measures of innovative activity in a class during the five years prior to investment: (1) the country's annual number of (eventually-granted) patent applications in the class, and (2) the country's annual number of citations to patents in the class.

More precisely, for each treated class and potential control class, we compute the squared log difference in the number of patents the country produced in the two classes during each of the five years prior to investment. We also do the same with the number of citations the country made to patents in the two classes. Finally, we sum these squared differences. Our matched control class is the one that minimizes this measure of distance.

Changes in patenting and citation activity around U.S. startup investments

Having defined treatment and control classes for a country, we estimate difference-in-differences specifications of the form:

$$ln(1 + y_{fct}) = \beta_1 Post_{fct} + \beta_2 Post_{fct} \times Treated_{fc} + \alpha_{fc} + \eta_t + \varepsilon_{fcd}, \tag{5.2}$$

where observations are at the country×patent-class×year level, with f indexing countries, c indexing technology classes, and t indexing years. We limit the sample to treated classes in the five years before and after the country's first investment in a U.S. startup specializing in the class, and matched control classes for the same country and time period. The two dependent variables that we explore are the log of one plus the number of patents by country f in patent class c applied for in year t, and the log of one plus the number of citations by country f to patent class c made by patents applied for in year t. The variable $Post_{fct}$ is an indicator equal to one in the year of investment and the five subsequent years; $Treated_{fc}$ is an indicator variable equal to one if the technology class c was one that the country f made a U.S. startup investment in; α_{fc} is a country-class pair fixed effect; and η_t is a year fixed effect. Standard errors are clustered at the country-class level.

The results are reported in Table 6. In Panel A, we examine changes in patenting activity around investment in a U.S. startup. In columns 1-2 (3-4) [5-6], we classify a country as having invested in a U.S. startup specializing in a particular technology class if a corporation based in that country invested in a U.S. startup that had any (the mode) [the majority] of its eventually-granted patent applications in that class at the time of investment. As discussed in Section 5.1.2, the U.S. switched

from the USPC patent classification scheme to the CPC scheme at the start of 2015. In the even columns, we use the USPC scheme (imputed by us after 2015); in the odd columns, we use the CPC scheme (imputed by the USPTO before 2015).

In column 1, we find that after investing in a U.S. startup with a patent in a particular USPC patent class, countries increase their patenting in that class by 17.1% relative to their patenting in the control class. In the remaining columns, we find similar results using the different definitions of patent classes and investments in a class discussed above. The point estimates range from 12.2% to 19.5% with all coefficients statistically significant at the 1% level.

In Panel B, we examine changes in citation activity around investment in a U.S. startup. In column 1, we find that after investing in a U.S. startup with a patent in a particular USPC patent class, countries increase their citations to patents in that class by 31.3% relative to their citations to the control class. In the remaining columns, we find point estimates ranging from 25.1% to 38.3%, with all coefficients statistically significant at the 1% level. Overall, these results suggest that foreign countries do learn from their investments in U.S. startups.

Alternative control group

As discussed earlier, however, a natural worry is the endogeneity of cross-border investments. One could envision a scenario where there is an exogenous shift in the technology opportunity set in both the U.S. and the foreign nation, to which the increase in corporate venturing and the boost in innovation are both responses, as in Manski (1993).

To further address this concern, we create an alternative control group in the same technology class. Specifically, rather than than comparing activity in treated classes to activity in different control classes within the same country, we instead compare activity in treated classes to activity in the same classes within a different control country that did not invest. Aside from changing the dimension held constant across the treatment and control groups, we continue to match the two in exactly the same way described previously.

Appendix Table A.1, shows the results. With this alternative control group that shares the same technology class, we continue find a strong positive association between CVC investments and subsequent patent and citation activity. The magnitudes are also similar to those found using our baseline specification. This helps somewhat to allays concerns about unobserved technology shocks.

Dynamics

Returning to our baseline specification, it is also interesting to examine the dynamics of a country's patenting in more detail over the years surrounding a U.S. startup investment. Therefore, rather than pooling together the years before investment and the years after investment, we examine each

of these years separately. Specifically, we estimate dynamic difference-in-differences specifications of the form:

$$ln(1 + y_{fct}) = \sum_{\tau=-5}^{5} \delta_\tau \mathbb{1}\{EventYear_{fct} = \tau\} + \sum_{\tau=-5}^{5} \beta_\tau \mathbb{1}\{EventYear_{fct} = \tau\} \times Treated_{fc} + \alpha_{fc} + \eta_t + \varepsilon_{fct} \tag{5.3}$$

Equation 5.3 is the same as equation 5.2, but with the variable $Post_{fct}$ replaced by a series of $EventYear_{fct}$ indicator variables. We define event years based on the year of investment (i.e., $EventYear_{fct} = 0$ corresponds to the year of investment) and the omitted year is the year prior to investment ($EventYear_{fct} = -1$). Table 7 and Figure 6 show the results, with Figure 6 corresponding to column 1 of Table 7. The coefficients on the interaction terms represent the difference between the treatment and control classes in each event year. From these coefficients, we see that in the five years leading up to a U.S. startup investment, there is no significant difference between a country's patenting in the treatment and control classes. In each of the five years following the investment, however, patenting in the treatment class is significantly higher than patenting in the control class. Again, these patterns are consistent with the idea that countries learn from U.S. startup investments.

Foreign direct investment

One additional concern may be that these corporate venture investments may be occurring simultaneously with more traditional foreign direct investment (FDI). FDI has been shown to be associated with knowledge flows in analyses such as Branstetter (2006), Javorcik (2004), and Keller and Yeaple (2009). However, it is important to note from the dynamic results that there is a discontinuity around the year of the first venture investment in a class. Therefore, our findings could not be explained by a general trend in FDI investment.

Nonetheless, to further address this concern, we re-run our analyses controlling for annual FDI flows into the U.S. at the country×year level.[27] Appendix Table A.2 shows that the results remain virtually unchanged after controlling for FDI. Thus, it is not the case that the jump in patenting activity that we observe around venture investments corresponds a simultaneous jump in FDI.

[27] These data were taken from the Bureau of Economic Analysis website and (in older years) their publication Survey of Current Business. In principle, one could also control for FDI flows into the U.S. at the country×industry×year level, but the data available from the BEA define industries too coarsely to map to patent classes and inconsistently employ different industry groupings.

Heterogeneity in learning by basicness of technology

As posited in the theoretical analysis, the basicness of a technology may also affect the extent of learning from a foreign corporate venture investment. In particular, fields that are closer to the academic frontier may have a lower level of baseline spillovers: it is harder to learn from the advanced research conducted at the frontier. In these settings, corporate venture investments may be more critical to learning.

To test this idea, we use the basicness measure defined in Section 5.1.2, which is based on the citations to academic research made by the patents in a class. In Table 8, we repeat the analysis of Table 6, now dividing observations by whether they are of patents with a primary assignment to a patent class above or below the median in terms of basicness.

As Panel A reports, the interactions between the post and treated indicators are significantly larger for patent classes with high basicness than for those with low basicness. Specifically, patents in high basicness treated classes increase by 23.3% after investment, whereas those in low basicness treated classes only increase by 10.6%, with the difference being statistically significant at the 1% level. Similarly, citations in high basicness treated classes increase by 47.7% after investment, whereas those in low basicness treated classes only increase by 14.5%, with the difference again being statistically significant at the 1% level.

Panel B of Table 8 shows the full dynamics. These results are also shown graphically in Figure 7. Again we do not see significant pre-trends for treated classes with either high or low basicness. However, when a company based in a foreign country invests in a U.S. startup specializing in a more basic class, we see a significantly greater increase in the patenting and citation activity in that class by the investing country.

A special look at Chinese investments

Many of the policy discussions cited in the introduction, as well as the motivating examples above, focus on investments in U.S. startups by corporations based in one nation in particular: China. It is natural to think that the concerns around spillovers and technology flows are far greater when the corporate investor is from a nation engaged in economic, political, and military competition with the country where the startup is based.

As the data description above suggested, Chinese corporate venture investments in U.S. startups are a relatively recent phenomenon. Thus, the number of such investments in the sample are relatively modest and the investment activities quite recent. Nonetheless, in Table 9 and Figure 8, we explore whether our results hold for Chinese investments. In particular, we replicate the results in Tables 6 and 7, as well as Figure 6, using the sub-sample.

The supplemental analyses reveal that the spillover results seen above are manifested in particularly dramatic form when it comes to Chinese investments in Silicon Valley. Comparing the coefficients

on the key independent variable in Tables 6 and 9, we see the predicted spillovers are substantially greater in the China-only analysis. For instance, comparing the first regressions in the two tables, the interaction of the treated and post dummy is associated with a 49 percent increase in patents in Table 9 (=exp(0.397)), but only a 19% boost in Table 6. These results indicate that the results above are not simply driven by technology flows between close allies.

Micro evidence

The results above establish that a foreign country's patent citations to a given technology class increase after a corporation based in that country invests in a U.S. startup specializing in that technology. It is natural to wonder whether the same phenomenon is seen on a more micro level as well.

To investigate this, Table 10 examines how citations from foreign corporations to the patents of the U.S. startups they invest in change following their investment. In this case, we do not have a natural control group, so we simply compare citation activity before investment to citation activity after investment. Observations are at the corporation×startup×year level. As before, we limit the sample to the five years before and after an investment—and also include the investment year itself.

Column (1) shows that there is a significant increase in the annual probability of a citation to a U.S. startup after the investment. The probability increases by 1.13 percentage points per year, which is a 226% increase relative to the pre-period mean. However, this large increase may partly be driven by the fact that some startups may not have had any granted patents to be cited prior to the investment. Therefore, in column (2) we restrict the sample to years in which the startup did have granted patents. With this restriction, the coefficient becomes to 3.69 percentage points, or a 93% increase relative to the pre-period mean. Thus, the probability of citing the startup still nearly doubles after investment. Finally, in column (3) we also include a full set of fixed effects for the number of granted patents the startup had as of the end of the year. We find similar effects.

In addition to comparing citations in the five years before the investment to citations in the five years after investment, we also examine the dynamics year-by-year. Figure 9 shows this analysis, which corresponds to column (2) of Table 10. As can be seen, we find a discrete jump in citation probability following an investment event, with little notable pre-trend leading up to the event.

Overall, this analysis provides more direct evidence of learning, as after investments, foreign corporations significantly increase the rate at which they cite the patents of the startups in which they invest.

5.2.3 Do U.S. startups benefit from foreign investments?

Most of our analysis thus far has focused on whether foreign corporations benefit from U.S. startup investments. We conclude by investigating whether there is any evidence that U.S. startups benefit

from these investments as well. In particular, as the model suggests, foreign investments may give financially constrained startups access to funding that they would not have been able to obtain otherwise. This funding may, in turn, allow them to innovate. We therefore examine whether there is a positive correlation between foreign CVC investments in U.S. startups focusing on a technology class and contemporaneous patenting in that class by U.S. venture-backed startups.

Specifically, we estimate equations of the form:

$$StartupActivity_{c,t} = \alpha + \beta ForeignInvestment_{c,t} + \varphi_c + \eta_t + \varepsilon_{ct}, \tag{5.4}$$

where $StartupActivity_{c,t}$ is one of four proxies for startup activity delineated below; $ForeignInvestment_{c,t}$ represents the log of total foreign CVC investments in U.S. startups in class c in year t ; φ_c represents class fixed effects; and η_t represents year fixed effects.

The results are shown in Table 11. We look at four metrics for U.S. startup activity. In columns 1–2, we look at the logarithm of the number of U.S. VC-backed startups patenting in class c in year t, looking first at new patenting entities only and then all startups. In columns 3–4, we look at the logarithm of the count of U.S. VC-backed startup patents in class c in year t. We again examine first patents by new patenting entities only and then those by all startups. We find a positive correlation between foreign investments in U.S. startups active in a technology class and patenting in that technology class by U.S. startups. While this evidence is open to alternative interpretations, it is at least suggestive of benefits to U.S. startups from foreign CVC investments.

6 Conclusion

This paper is motivated by the intense policy interest in foreign investments in startup firms, especially in Silicon Valley. Despite the intense real world interest, the topic has attracted very little attention in the economics literature.

This paper examines foreign corporate investments in Silicon Valley from a theoretical and empirical perspective. We model a stylized setting where startups can attract investment from foreign corporations, which may allow young firms to pursue innovations for which they would otherwise be unable to raise financing. But these investments may lead to knowledge spillovers to the foreign corporation and its nation. We present empirical results consistent with the presence of knowledge spillovers to foreign investors.

The analysis raises a number of avenues for future research. One possibility would be to enrich the depiction of the relationship between the foreign corporation and the startup. For instance, the involvement of the corporation with the startup might bring additional benefits, such as enhanced market access to the foreign nation for the startup and deeper ties to the startup's venture backers for the corporation. The easing of the startups' financial constraints through foreign corporate investments might be more or less consequential, depending on the boom/bust cycle of venture

financing. More generally, policies to modulate foreign corporate investments must be seen in the context of a broader array of policies affecting the competitive positioning of startups. Examples include limits on the ability of domestic firms to readily hire foreign engineers to provisions in patent policy that favor or harm young firms.

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Figure 1
Entry and Cross-border Investment
The figure shows the possibilities associated with entry in a given industry in the leader country (the U.S. in this case).

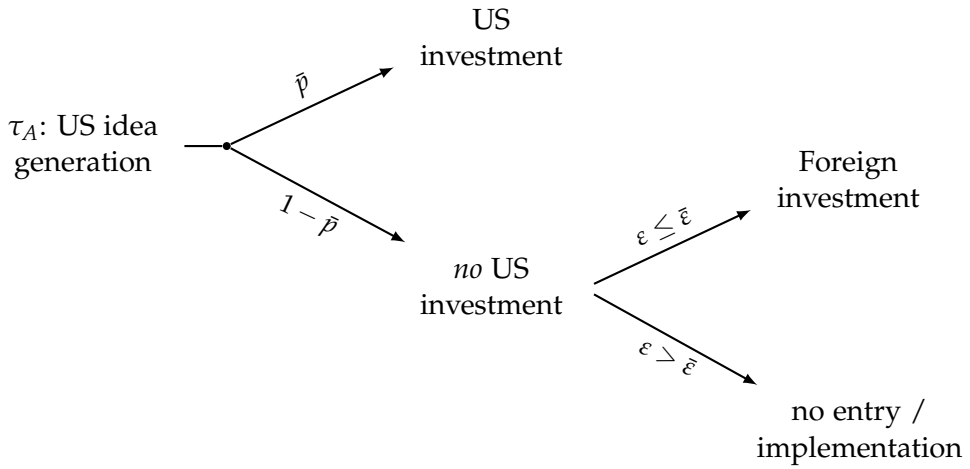


Figure 2

Cross-Border Investment Decisions and the Effect of Basicness

Panel A shows the investment probabilities conditional on the chance to do so arises (the idea abroad is not domestically funded). Panel B compares two hypothetical economies: the calibrated one and another one, in which the baseline spillover rate is lower (operating in more basic sectors). The line shows the difference in the investment probabilities (conditional on idea arrival) of laggards that did not invest in VC yet in both economies. Positive values mean the probability is higher in the alternative economy.

(a) **Investment Probability (conditional on idea arrival)** (b) **Difference in Investment Probability (higher basicness)**

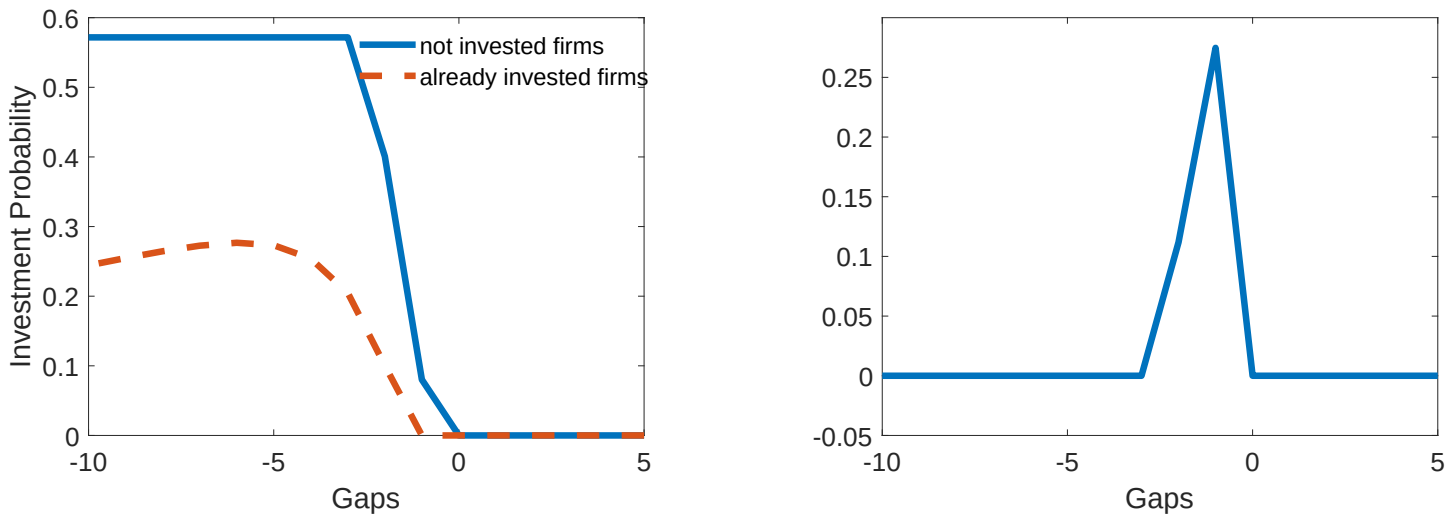
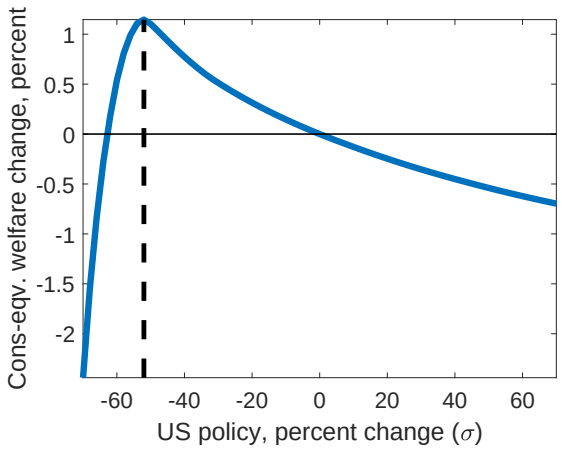


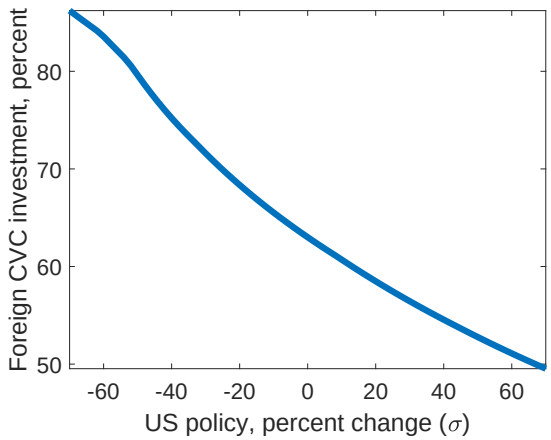
Figure 3
Policy Analysis

Panel A shows the shows the change in consumption-equivalent welfare as σ moves from -0.70 to 0.70. Panels B, C, and D show similar patterns for the foreign CVC share, growth, and security cost.

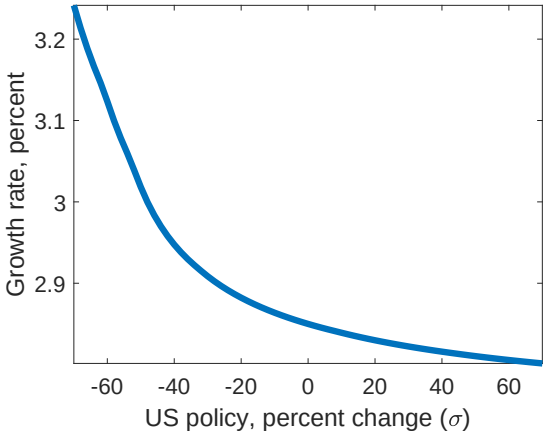
(a) **Consumption-Equivalent Welfare**



(b) **Foreign CVC Share**



(c) **Growth**



(d) **Security Cost**

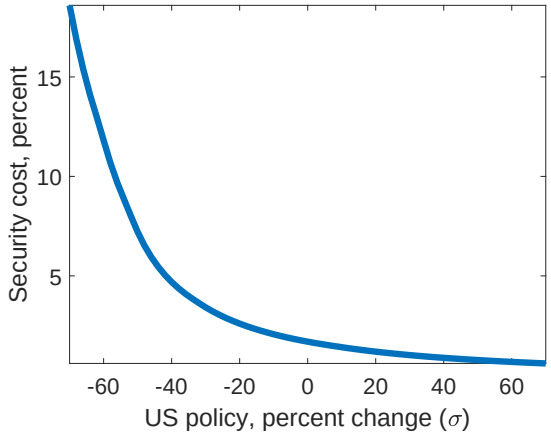
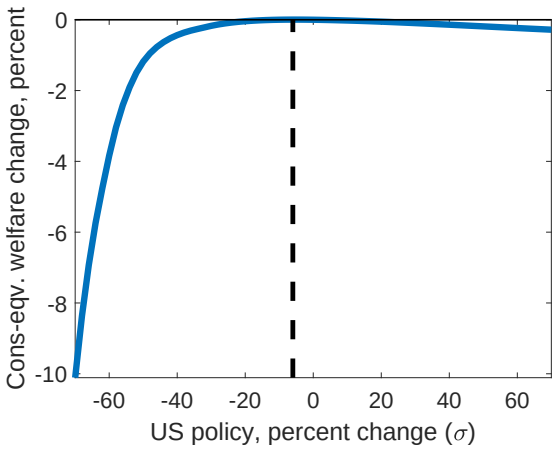


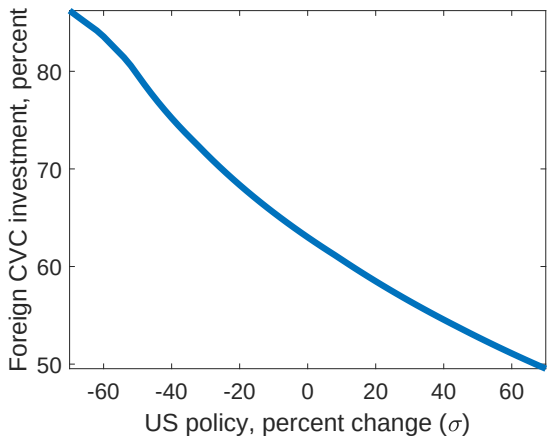
Figure 4
Policy Analysis with Higher Cost of Security

Panel A shows the shows the change in consumption-equivalent welfare as σ moves from -0.70 to 0.70, but now with $\chi_0 = 3.85$. Panels B, C, and D show similar patterns for the foreign CVC share, growth, and security cost.

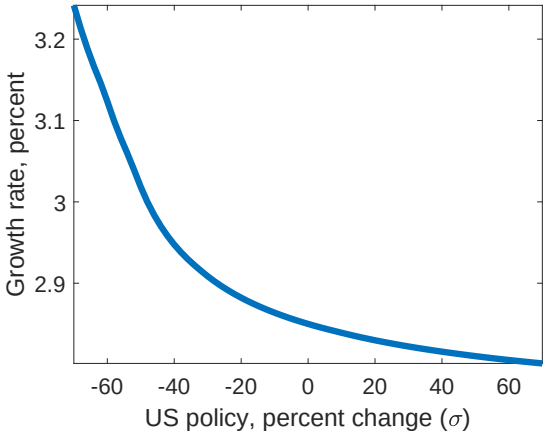
(a) **Consumption-Equivalent Welfare**



(b) **Foreign CVC Share**



(c) **Growth**



(d) **Security Cost**

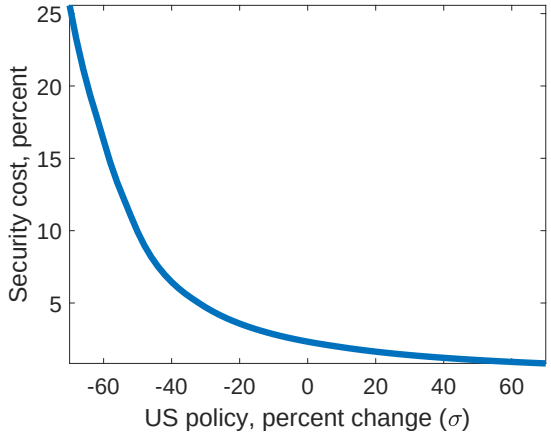


Figure 5
Corporate VC Investment Share

Panel A of this figure depicts the share of all U.S. VC investment attributable to foreign CVCs over time. Panel B depicts the share of all U.S. VC investment attributable to all CVCs. Panel C depicts the share of U.S. CVC investment attributable to foreign CVCs.

Panel A: Foreign CVC Investment / VC Investment

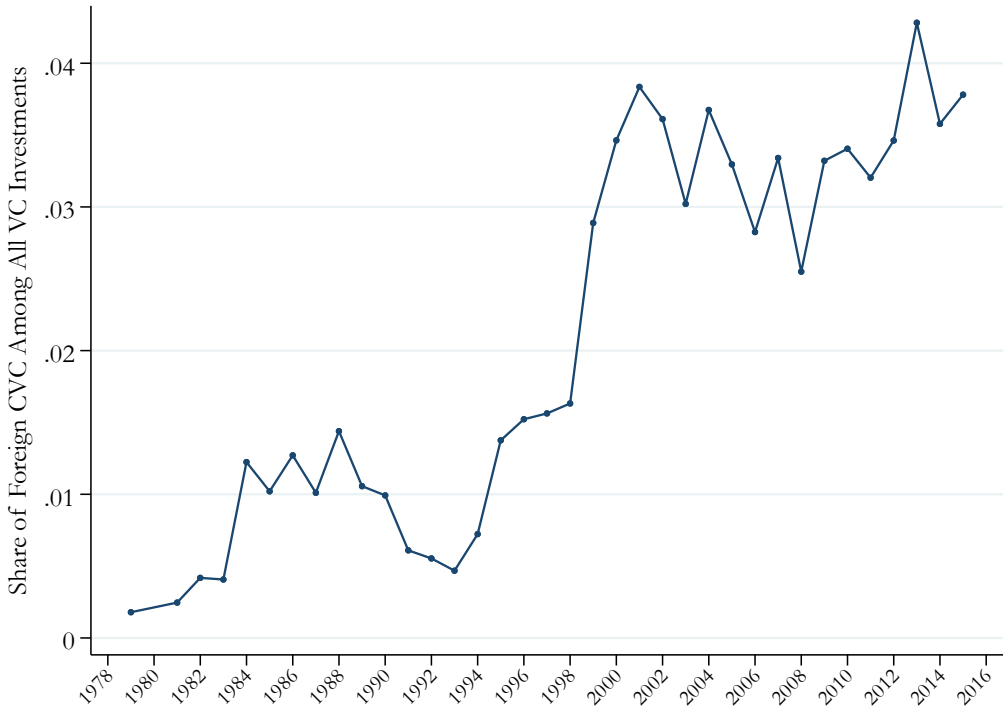
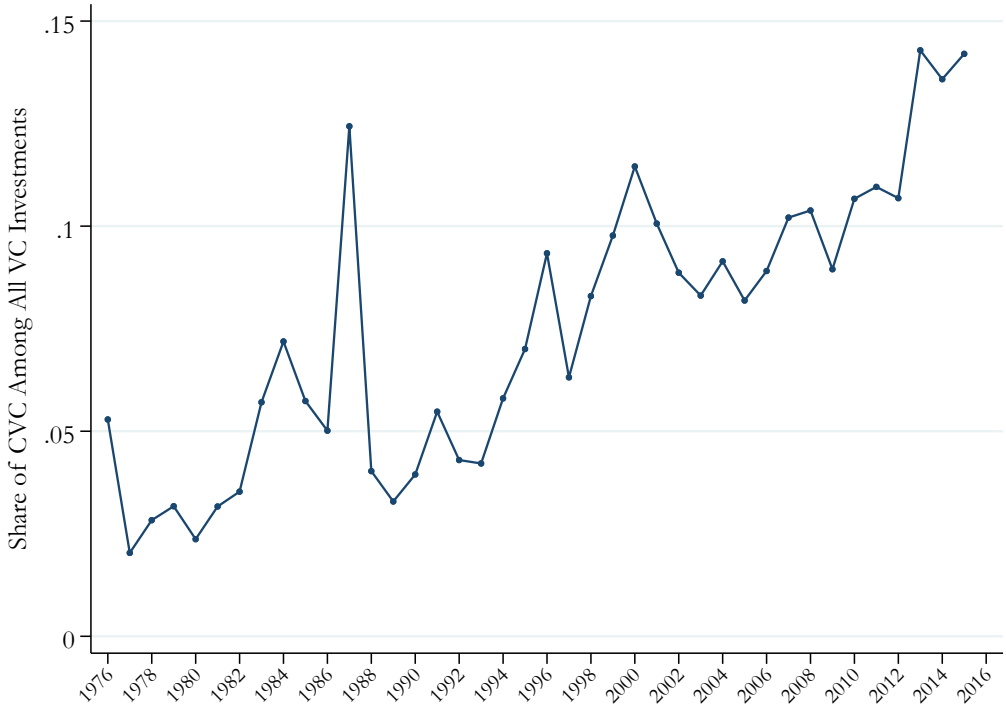


Figure 5
(Continued}
Panel B: CVC Investment / VC Investment



Panel C: Foreign CVC Investment / CVC Investment

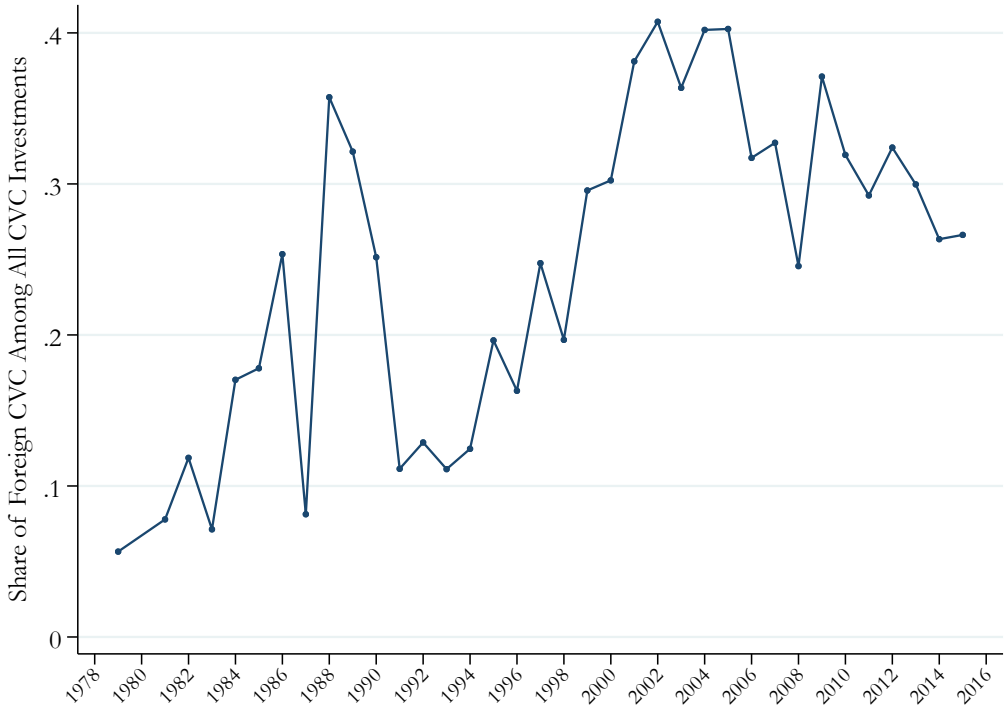
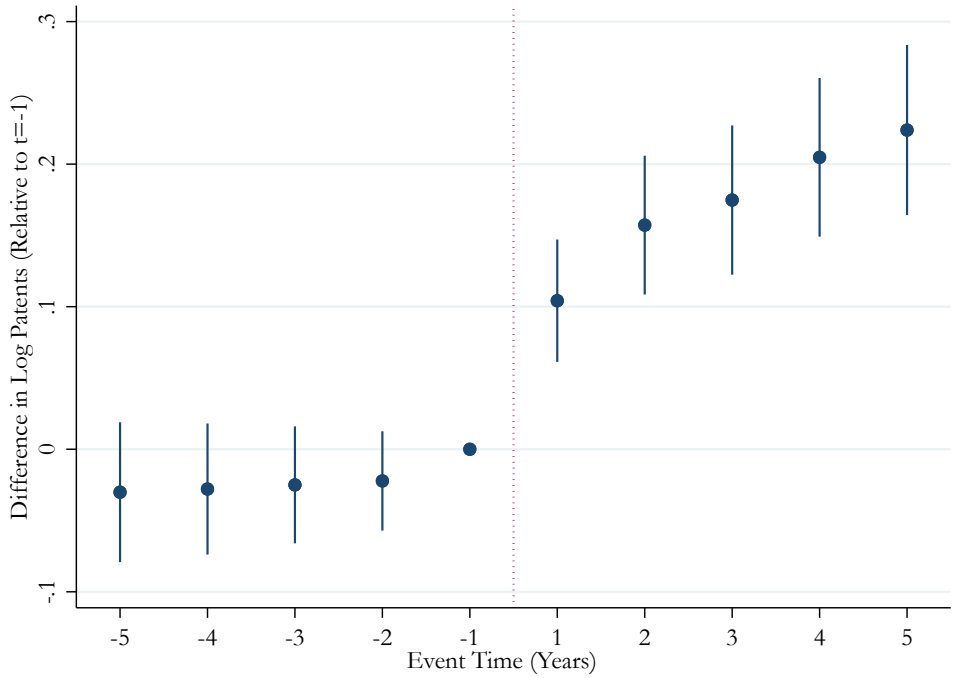


Figure 6

Innovation Patterns around Investments by Foreign Corporations—Dynamics

This figure shows the results of Table 7 graphically. Panel A corresponds to column (1) of Panel A of Table 7. Panel B corresponds to column (1) of Panel B of Table 7.

Panel A: Patents



Panel B: Citations

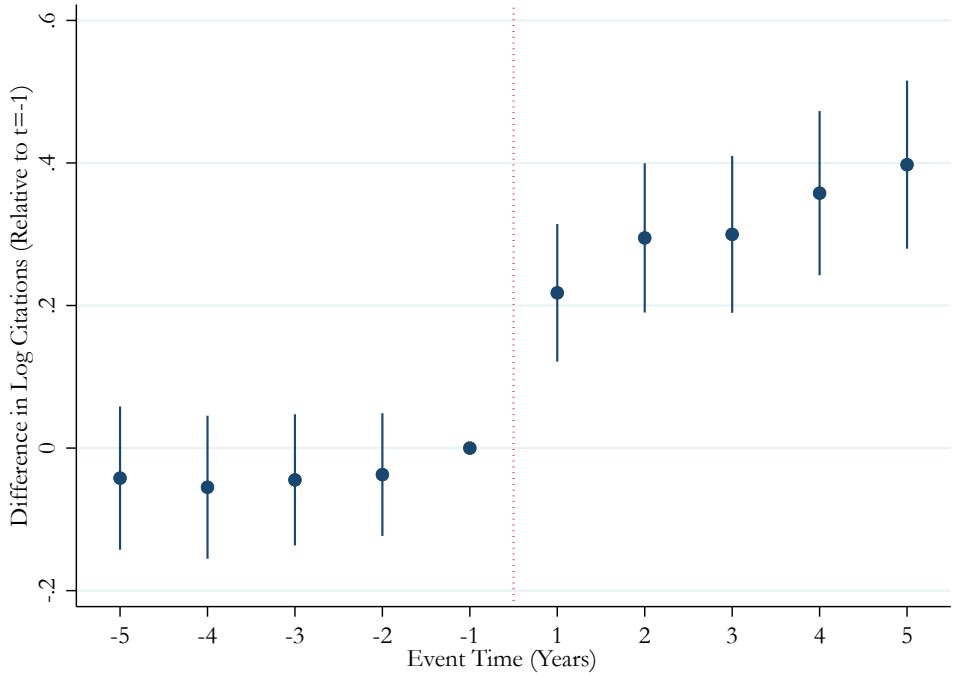
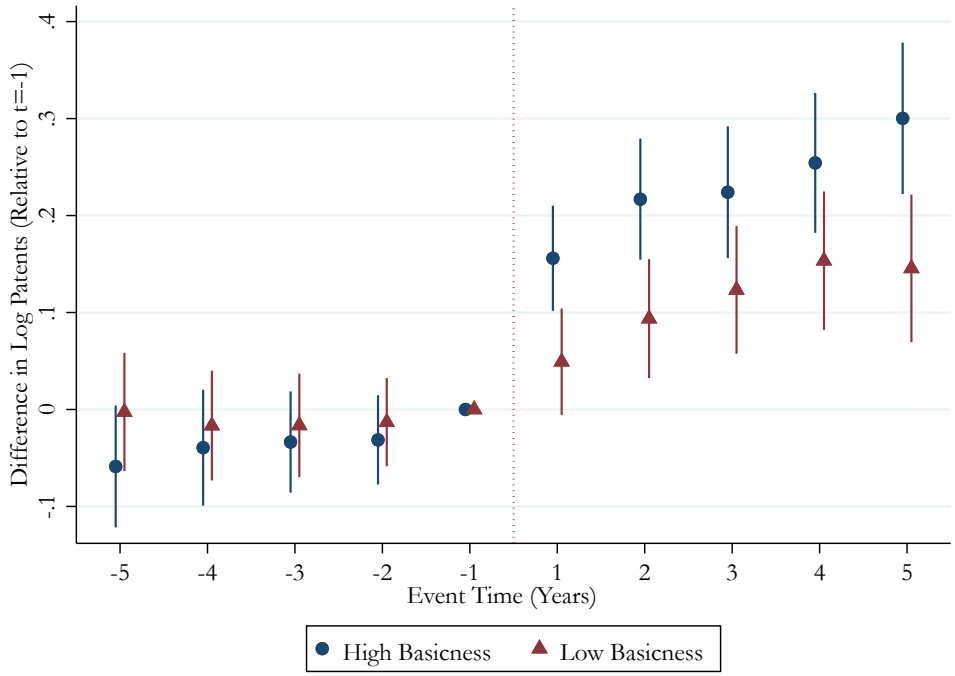


Figure 7
Dynamics by Patent Class Basicness

This figure shows the results of Table 8 (Panel B) graphically. Panel A displays the coefficients of the first two regressions; Panel B, those of the next two.

Panel A: Patents



Panel B: Citations

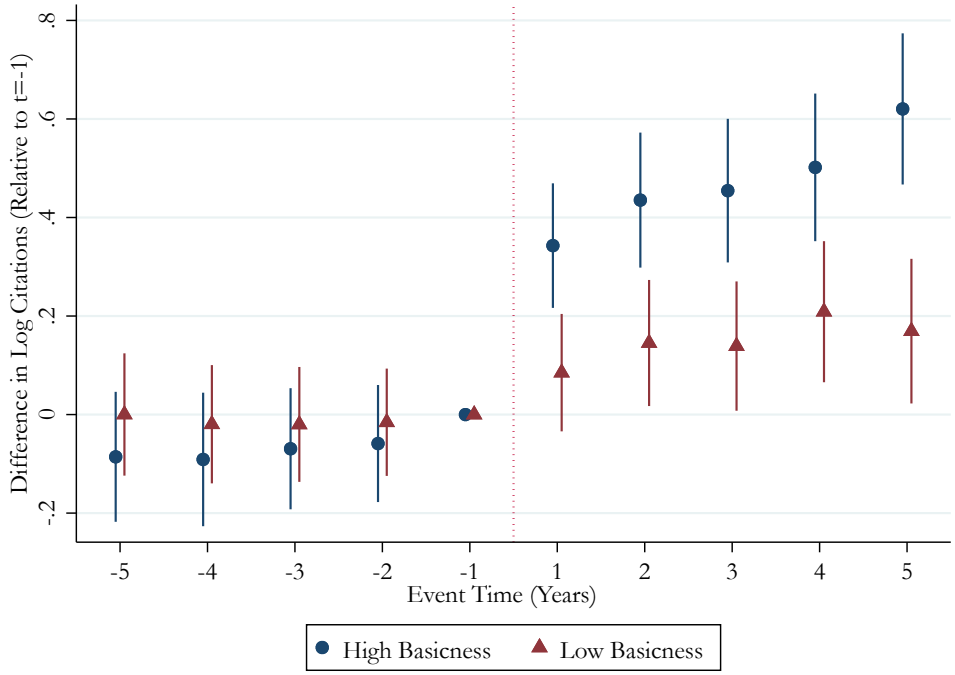
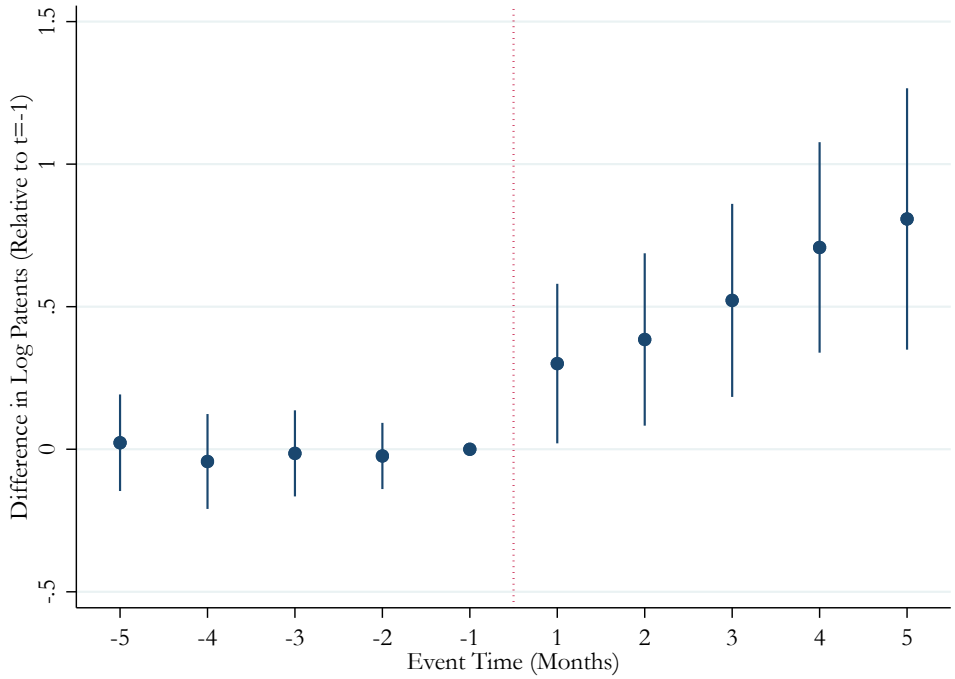


Figure 8

Innovation Patterns around Investments by Foreign Corporations—China

This figure shows the results of Table 9 graphically. Panel A corresponds to column (2) and Panel B corresponds to column (4).

Panel A: Patents



Panel B: Citations

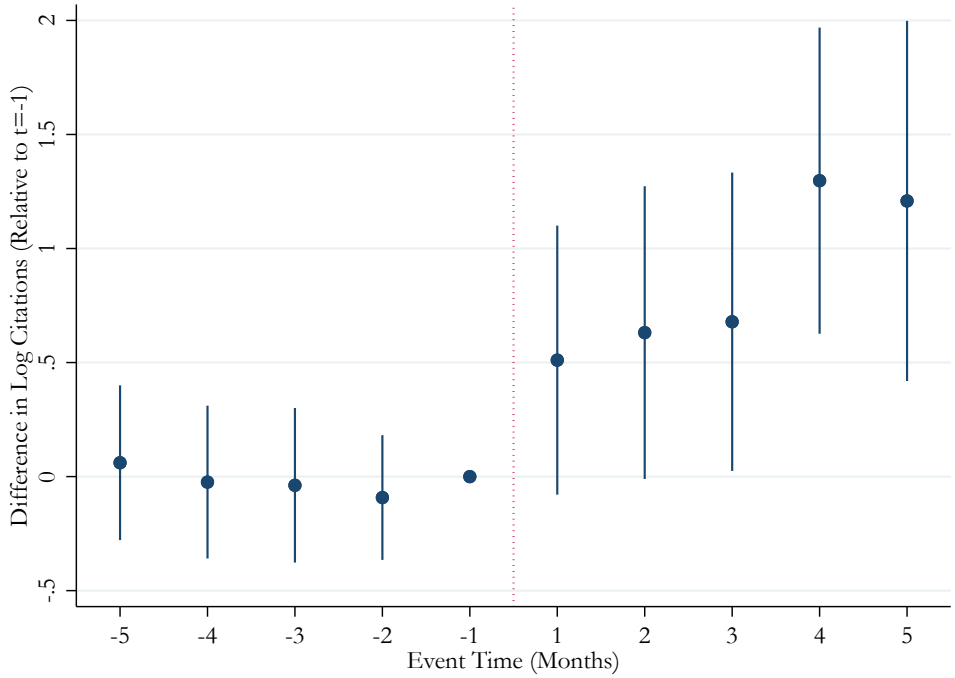


Figure 9

Dynamics: Citations from Foreign Corporations to U.S. Startups They Invest In

This figure shows the results of Table 10 (Column 2) graphically year-by-year.

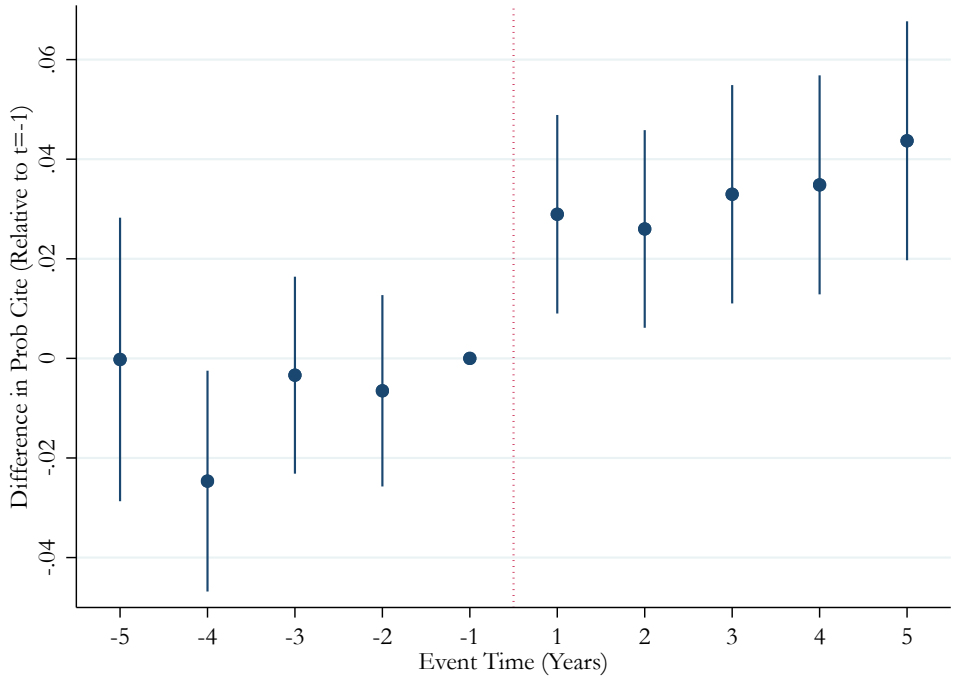


Table 1
Parameter Values

This table presents values and sources for the externally calibrated coefficients, as well as the values of the internally calibrated ones.

Parameter	Description	Value	Identification*
	Externally calibrated		
ρ	Subjective rate of time preference	0.03	U.S. long-run interest rate
τ_A	Entry in country A	0.63	Share of patents by U.S. entities†
τ_B	Entry in country B	0.37	Share of patents by foreign entities†
δ_0	Baseline spillover	0.50	Literature on international spillovers
δ	Investment spillover	0.55	Patenting intensity of treated firms
ϕ	Probability of quick catch-up	2.5%	Top-cited share among patents firms
Δ	Profits retained by investor	50%	Set for illustrative purposes
$\bar{m}$	Max. technology gap	30	Set for illustrative purposes
	Internally calibrated		
λ	Step size	1.056	Set to fit moments in Table 2
α	CES technology	0.983	Set to fit moments in Table 2
$\bar{p}$	Probability of domestic financing	9.3%	Set to fit moments in Table 2
u_ε	Investment cost (upper bound)	0.17	Set to fit moments in Table 2

*For the values of the empirical targets, see the discussion in the text and Table 2.

†Patent counts are obtained from the USPTO data and are weighted by the total number of citations each patent has received. Citations are computed relative to all other patents issued in the same quarter and assigned to the same four-digit CPC patent class and in patents issued through October 2019.

Table 2
Model Fit

This table presents values of the empirical data for the moments, as well as the predicted values.

Moment	Data	Model
U.S. growth rate	2.85%	2.85%
Non-business corporate profit share of GDP	5.9%	5.9%
Share of patenting U.S. firms receiving VC	25%	25%
Fraction of foreign VC in total VC inv. in patenting firms	63%	63%

Table 3
Sensitivity to Alternative Parameter Choices

This table shows the optimal government policy (σ^*) in each of the four alternative economies. For both δ_0 and Δ, we experiment with the values 0.30 and 0.70 (the calibrated value for both parameters is 0.50).

	Low Spillover	**High Spillover**	**Low Profit**	**High Profit**	**Benchmark Economy**
Optimal Policy σ^*	-48%	-10%	-36%	-24%	-52%

Table 4
Summary Statistics

This table presents summary statistics for our key variables as defined in Section 5.1.2. Observations are at the country×patent-class×year level. Summary statistics for investment measures are computed using observations with positive investments in a technology class from a country in a given year. Summary statistics for patent measures are computed using all possible country×technology class pairs for all the years with positive aggregate patenting by the country.

	Mean	Std	Median
Annual CVC investments in class by foreign country (in $ thous)	9650.3	26584.4	2545.5
Aggregate annual CVC investments by foreign country (in $ thous)	163790	255813	64924
Annual patent applications in class by foreign country	13.04	58.23	2
Aggregate annual patent applications by foreign country	4057.0	8198.3	1105
Annual patent applications in class by all U.S. VC startups	36.29	132.94	4
Aggregate annual patents application by all U.S. VC startups	7862.7	7321.3	5582
Backwards academic citations in class	1302.83	11495.05	13
Relative knowledge of foreign country with respect to U.S. in class	.050	.094	.015

Table 5
Determinants of Cross-Border Investment

This table examines how investments by corporations based in a foreign nation in U.S. startups in that technology reflects the relative knowledge of that nation. Observations are at the patent class by country by year level. In the first two columns, the dependent variable is an indicator of whether at least one corporate venture capital program from country f invested in U.S. startups that innovate in a technology class c in year t. In the last two columns, the dependent variable is the share of investments in U.S. startups that innovate in a technology class c in year t by CVC firms from a country f relative to all investments in U.S. startups by CVCs from f in year t. *Relative knowledge* is a ratio with a numerator equal to number of successful patent applications submitted by foreign assignees from country f in technology class c before the investment event at t. The denominator is the sum of all successful patent applications submitted by foreign assignees from f *and* from the U.S. in technology class c before year t. 1st and 2nd lags look at this variable one year and two years before the investment event correspondingly. Patent classes are defined using the USPC patent classification scheme. Robust standard errors in parentheses clustered on year and country levels. *** p<0.01, ** p<0.05, * p<0.1

	$\mathbb{1}\{\text{Investment}_t\}$		Investment Share$_t$	
	(1)	(2)	(3)	(4)
Relative Knowledge$_{f,c,t}$	-0.103***	-0.173***	-0.0043**	-0.0051**
	(0.039)	(0.046)	(0.0017)	(0.0021)
Relative Knowledge$_{f,c,t-1}$		-0.089		-0.0007
		(0.092)		(0.0046)
Relative Knowledge$_{f,c,t-2}$		0.137		0.0002
		(0.140)		(0.0059)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R-squared	0.040	0.040	0.002	0.005
Observations	71,646	56,108	71,646	56,108

Table 6

Innovation Patterns around Investments by Foreign Corporations—Difference-in-Differences

This table examines how a foreign country's patenting evolves after a corporation based in that nation invests in a U.S. startup specializing in that technology. Observations are at the patent class by country by year level. The sample consists of the five years before and after the first investment of a company based in that country in a U.S. startup specializing in a particular technology class. Changes in the country's innovative activity in that "treated" technology class are compared to changes in the same country's innovative activity in a similar "control" technology class that it never invested in. Treated classes are matched to control classes based on two measures of innovative activity in a class during the five years prior to investment: (1) the country's annual number of (eventually-granted) patent applications in the class, and (2) the country's annual number of citations to patents in the class. In columns 1-2 (3-4) [5-6], a country is classified as having invested in a U.S. startup specializing in a technology class if a corporation based in that country invested in a U.S. startup that had any (the mode) [the majority] of its eventually-granted patent applications in that class at the time of investment. In Panel A, the dependent variable is Log(1+$Patents_{fct}$), where $Patents_{fct}$ represents the number of patents country f applied for in class c in year t. In Panel B, the dependent variable is Log(1+$Citations_{fct}$), where $Citations_{fct}$ represents the number of citations by country f to patents in class c in year t. $Post_{fct}$ is an indicator equal to one in the year of investment and the five subsequent years; $Treated_{fc}$ is an indicator variable equal to one if the technology class c was one that the country f made a U.S. startup investment in; Country×Class FE represents country-by-class fixed effects; and Year FE represents year fixed effects. In the even columns, the USPC patent classification scheme is used; in the odd columns, the CPC patent classification scheme is used. Robust standard errors in parentheses are clustered at the country-class level. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Patents

	Log(1+Patents)					
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	0.171***	0.122***	0.178***	0.195***	0.179***	0.189***
	(0.0183)	(0.0193)	(0.0300)	(0.0341)	(0.0322)	(0.0374)
Country × Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Class Type	USPC	CPC	USPC	CPC	USPC	CPC
Treatment Type	Any	Any	Mode	Mode	Majority	Majority
R^2	0.912	0.918	0.934	0.932	0.934	0.935
Observations	38,678	33,928	14,698	12,370	12,166	10,294

Panel B: Citations

	Log(1+Citations)					
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	0.313***	0.251***	0.317***	0.383***	0.329***	0.353***
	(0.0315)	(0.0329)	(0.0491)	(0.0553)	(0.0528)	(0.0593)
Country × Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Class Type	USPC	CPC	USPC	CPC	USPC	CPC
Treatment Type	Any	Any	Mode	Mode	Majority	Majority
R^2	0.842	0.852	0.877	0.879	0.877	0.887
Observations	38,678	33,928	14,698	12,370	12,166	10,294

Table 7

Innovation Patterns around Investments by Foreign Corporations—Dynamics

This table repeats the analysis of Table 6, but rather than pooling together the years before investment and the years after investment, it examines each of these years separately. We define event years based on the year of investment (i.e., $EventYear_{fct} = 0$ corresponds to the year of investment) and the omitted year is the year prior to investment ($EventYear_{fct} = -1$). *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Patents

	Log(1+Patents)					
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × 𝟙(Event Year=-5)	-0.0301	-0.0276	-0.0389	-0.0343	-0.0531	-0.0405
	(0.0224)	(0.0225)	(0.0343)	(0.0374)	(0.0384)	(0.0414)
Treated × 𝟙(Event Year=-4)	-0.0279	-0.0228	-0.0317	-0.0550	-0.0448	-0.0587
	(0.0210)	(0.0208)	(0.0337)	(0.0349)	(0.0377)	(0.0388)
Treated × 𝟙(Event Year=-3)	-0.0250	-0.0177	-0.0237	-0.0437	-0.0262	-0.0459
	(0.0190)	(0.0194)	(0.0294)	(0.0320)	(0.0324)	(0.0347)
Treated × 𝟙(Event Year=-2)	-0.0222	-0.0249	-0.00884	-0.0216	-0.0283	-0.00976
	(0.0165)	(0.0181)	(0.0259)	(0.0288)	(0.0295)	(0.0311)
Treated × 𝟙(Event Year=0)	0.0681***	0.0705***	0.0880***	0.0945***	0.0889***	0.0689**
	(0.0171)	(0.0184)	(0.0260)	(0.0290)	(0.0292)	(0.0310)
Treated × 𝟙(Event Year=1)	0.104***	0.0745***	0.140***	0.120***	0.117***	0.111***
	(0.0197)	(0.0206)	(0.0310)	(0.0337)	(0.0341)	(0.0370)
Treated × 𝟙(Event Year=2)	0.157***	0.104***	0.158***	0.169***	0.149***	0.157***
	(0.0223)	(0.0239)	(0.0339)	(0.0383)	(0.0370)	(0.0423)
Treated × 𝟙(Event Year=3)	0.175***	0.121***	0.150***	0.177***	0.151***	0.188***
	(0.0241)	(0.0251)	(0.0384)	(0.0424)	(0.0420)	(0.0459)
Treated × 𝟙(Event Year=4)	0.205***	0.115***	0.221***	0.185***	0.206***	0.188***
	(0.0259)	(0.0277)	(0.0426)	(0.0478)	(0.0468)	(0.0520)
Treated × 𝟙(Event Year=5)	0.224***	0.149***	0.218***	0.274***	0.209***	0.269***
	(0.0279)	(0.0297)	(0.0440)	(0.0511)	(0.0481)	(0.0561)
Country × Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Class Type	USPC	CPC	USPC	CPC	USPC	CPC
Treatment Type	Any	Any	Mode	Mode	Majority	Majority
R^2	0.912	0.918	0.934	0.933	0.934	0.936
Observations	38,678	33,928	14,698	12,370	12,166	10,294

Table 7
(Continued)

Panel B: Citations

	Log(1+Citations)					
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × 𝟙(Event Year=-5)	-0.0421	-0.0404	-0.0536	-0.0661	-0.0669	-0.0890
	(0.0463)	(0.0476)	(0.0677)	(0.0738)	(0.0744)	(0.0811)
Treated × 𝟙(Event Year=-4)	-0.0549	-0.0257	-0.0567	-0.0838	-0.0816	-0.0964
	(0.0462)	(0.0457)	(0.0695)	(0.0733)	(0.0780)	(0.0786)
Treated × 𝟙(Event Year=-3)	-0.0446	-0.0240	-0.0417	-0.0850	-0.0361	-0.108
	(0.0432)	(0.0429)	(0.0618)	(0.0678)	(0.0686)	(0.0726)
Treated × 𝟙(Event Year=-2)	-0.0372	-0.0181	-0.0122	-0.0427	-0.0186	-0.0320
	(0.0411)	(0.0422)	(0.0601)	(0.0648)	(0.0690)	(0.0701)
Treated × 𝟙(Event Year=0)	0.151***	0.209***	0.176***	0.247***	0.225***	0.171**
	(0.0405)	(0.0428)	(0.0614)	(0.0669)	(0.0689)	(0.0687)
Treated × 𝟙(Event Year=1)	0.218***	0.171***	0.291***	0.252***	0.257***	0.191**
	(0.0444)	(0.0459)	(0.0675)	(0.0736)	(0.0744)	(0.0801)
Treated × 𝟙(Event Year=2)	0.295***	0.215***	0.271***	0.338***	0.303***	0.301***
	(0.0479)	(0.0514)	(0.0717)	(0.0781)	(0.0782)	(0.0856)
Treated × 𝟙(Event Year=3)	0.300***	0.260***	0.244***	0.341***	0.252***	0.331***
	(0.0501)	(0.0522)	(0.0754)	(0.0820)	(0.0830)	(0.0867)
Treated × 𝟙(Event Year=4)	0.358***	0.244***	0.395***	0.331***	0.379***	0.313***
	(0.0529)	(0.0551)	(0.0846)	(0.0881)	(0.0935)	(0.0947)
Treated × 𝟙(Event Year=5)	0.398***	0.296***	0.377***	0.499***	0.350***	0.477***
	(0.0543)	(0.0584)	(0.0814)	(0.0889)	(0.0892)	(0.0956)
Country × Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Class Type	USPC	CPC	USPC	CPC	USPC	CPC
Treatment Type	Any	Any	Mode	Mode	Majority	Majority
R^2	0.842	0.852	0.877	0.879	0.877	0.887
Observations	38,678	33,928	14,698	12,370	12,166	10,294

Table 8
Heterogeneity by Basicness of Patent Classes

This table examines whether the baseline results of Table 6 vary across patent classes that differ in their basicness. *High Basicness* is an indicator equal to one if class c is above the median in terms of the number of backward academic citations in its patent applications submitted at time t. *Low Basicness* is defined similarly. The sample and all other variables are defined as in Table 6. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Difference-in-Differences

	Log(1+Patents)		Log(1+Citations)	
	(1) Low Basicness	(2) High Basicness	(3) Low Basicness	(4) High Basicness
Treated × Post	0.106***	0.233***	0.145***	0.477***
	(0.0253)	(0.0261)	(0.0425)	(0.0458)
Country × Class FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
P-Value of Difference	0.001	0.001	0.000	0.000
Class Type	USPC	USPC	USPC	USPC
Treatment Type	Any	Any	Any	Any
R^2	0.920	0.902	0.857	0.825
Observations	19,436	19,242	19,436	19,242

Panel B: Dynamics

	Log(1+Patents)		Log(1+Citations)	
	(1) Low Basicness	(2) High Basicness	(3) Low Basicness	(4) High Basicness
Treated × $\mathbb{1}$(Event Year=-5)	-0.00255	-0.0587*	0.000171	-0.0858
	(0.0311)	(0.0320)	(0.0633)	(0.0673)
Treated × $\mathbb{1}$(Event Year=-4)	-0.0166	-0.0394	-0.0197	-0.0911
	(0.0288)	(0.0305)	(0.0612)	(0.0691)
Treated × $\mathbb{1}$(Event Year=-3)	-0.0164	-0.0336	-0.0200	-0.0694
	(0.0272)	(0.0266)	(0.0595)	(0.0627)
Treated × $\mathbb{1}$(Event Year=-2)	-0.0131	-0.0313	-0.0156	-0.0588
	(0.0232)	(0.0235)	(0.0555)	(0.0606)
Treated × $\mathbb{1}$(Event Year=0)	0.0413*	0.0939***	0.0799	0.219***
	(0.0240)	(0.0245)	(0.0544)	(0.0599)
Treated × $\mathbb{1}$(Event Year=1)	0.0492*	0.156***	0.0851	0.343***
	(0.0280)	(0.0277)	(0.0608)	(0.0645)
Treated × $\mathbb{1}$(Event Year=2)	0.0937***	0.217***	0.145**	0.435***
	(0.0313)	(0.0318)	(0.0652)	(0.0699)
Treated × $\mathbb{1}$(Event Year=3)	0.123***	0.224***	0.139**	0.455***
	(0.0336)	(0.0346)	(0.0669)	(0.0743)
Treated × $\mathbb{1}$(Event Year=4)	0.153***	0.254***	0.209***	0.502***
	(0.0364)	(0.0368)	(0.0730)	(0.0764)
Treated × $\mathbb{1}$(Event Year=5)	0.146***	0.300***	0.169**	0.620***
	(0.0388)	(0.0398)	(0.0748)	(0.0782)
Country × Class FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Class Type	USPC	USPC	USPC	USPC
Treatment Type	Any	Any	Any	Any
R^2	0.920	0.903	0.857	0.826
Observations	19,436	19,242	19,436	19,242

Table 9

Innovation Patterns around Investments by Foreign Corporations—China

This table repeats the analyses from Tables 6 and 7, limiting the sample to investments in U.S. startups by corporations based in China. Robust standard errors in parentheses are clustered at the country-class level.*** p<0.01, ** p<0.05, * p¡0.1.

	Log(1+Patents)		Log(1+Cites)	
	(1)	(2)	(3)	(4)
Treated × Post	0.397***		0.631***	
	(0.114)		(0.195)	
Treated × 𝟙(Event Year=-5)		0.0229		0.0608
		(0.0860)		(0.172)
Treated × 𝟙(Event Year=-4)		-0.0429		-0.0241
		(0.0845)		(0.170)
Treated × 𝟙(Event Year=-3)		-0.0145		-0.0382
		(0.0767)		(0.172)
Treated × 𝟙(Event Year=-2)		-0.0236		-0.0919
		(0.0589)		(0.139)
Treated × 𝟙(Event Year=0)		0.0722		0.108
		(0.0856)		(0.201)
Treated × 𝟙(Event Year=1)		0.300**		0.511*
		(0.142)		(0.300)
Treated × 𝟙(Event Year=2)		0.385**		0.631*
		(0.154)		(0.326)
Treated × 𝟙(Event Year=3)		0.522***		0.679**
		(0.172)		(0.332)
Treated × 𝟙(Event Year=4)		0.708***		1.297***
		(0.187)		(0.341)
Treated × 𝟙(Event Year=5)		0.808***		1.208***
		(0.233)		(0.401)
Country × Class FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Class Type	USPC	USPC	USPC	USPC
Treatment Type	Any	Any	Any	Any
R^2	0.885	0.889	0.842	0.846
Observations	1,940	1,940	1,940	1,940

Table 10

Citations from Foreign Corporations to the U.S. Startups They Invest In

Observations are at the corporation×startup×year level. The sample consists of the five years before and after an investment in a U.S. startup. The dependent variable is an indicator for whether the corporation cited a patent of the startup that year. The post investment variable is an indicator for the five years after the investment. All specifications have corporation×startup fixed effects; the third regression has fixed effects for the count of startup's patents. Robust standard errors in parentheses are clustered at the corporation×startup level. *** p<0.01, ** p<0.05, * p<0.1.

	$\mathbb{1}$(Corp. Cited Startup Patent)		
	(1)	(2)	(3)
$\mathbb{1}$(Post Investment)	0.0113***	0.0369***	0.0215***
	(0.00147)	(0.00984)	(0.00830)
Corp. × Startup FE	Yes	Yes	Yes
Startup Patent Count FE	No	No	Yes
Startups	All	With Patents	With Patents
Pre-Period Mean	0.005	0.040	0.040
R^2	0.400	0.529	0.530
Observations	34,780	6,954	6,954

Table 11
Foreign Investment and U.S. Startup Activity

Observations are at the patent class by year level. *New startups* are U.S. VC-backed startups with their first patent submitted in year t in class c. *All active* are all active VC-backed U.S. startups that have submitted at least one patent as of year t in class c. For these firms, we compute the logarithm of one plus the number of patenting U.S. startups and the number of patents in class c filed by U.S. startups in year t. Investments are measured as the log of one plus total foreign CVC investments in class c in year t measured in thousands of U.S. dollars. Patent classes are defined using the USPC patent classification scheme. Robust standard lerrors in parentheses are clustered at the patent class level. *** p<0.01, ** p<0.05, * p<0.1

	Log Number of Patenting U.S. Startups		Log Number of U.S. Startup Patents	
	New startups	All active	New startups	All active
	(1)	(2)	(3)	(4)
Log Foreign Investment	0.1170***	0.0167***	0.1195***	0.0214***
	(0.0101)	(0.0030)	(0.0102)	(0.0035)
Class FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R-squared	0.371	0.620	0.372	0.670
Observations	13,915	13,915	13,915	13,915

Internet Appendix

A Supplemental Tables

Table A.1
Difference-in-Differences with Alternative Control Group

This table repeats the analysis of Table 6 using an alternative control group. Rather than than comparing activity in treated classes to activity in different control classes within the same country, we instead compare activity in treated classes to activity in the same classes within a different control country that did not invest. Aside from changing the dimension held constant across the treatment and control groups, we proceed in the same way as in Table 6. Standard errors are clustered at the country-class level. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Patents

	Log(1+Patents)					
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	0.147***	0.126***	0.157***	0.138***	0.159***	0.142***
	(0.0182)	(0.0191)	(0.0301)	(0.0340)	(0.0329)	(0.0372)
Country × Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Class Type	USPC	CPC	USPC	CPC	USPC	CPC
Treatment Type	Any	Any	Mode	Mode	Majority	Majority
R^2	0.916	0.921	0.936	0.934	0.936	0.939
Observations	38,678	33,928	14,698	12,370	12,166	10,294

Panel B: Citations

	Log(1+Citations)					
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	0.298***	0.239***	0.314***	0.226***	0.322***	0.217***
	(0.0313)	(0.0322)	(0.0483)	(0.0545)	(0.0534)	(0.0601)
Country × Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Class Type	USPC	CPC	USPC	CPC	USPC	CPC
Treatment Type	Any	Any	Mode	Mode	Majority	Majority
R^2	0.852	0.863	0.887	0.887	0.887	0.896
Observations	38,678	33,928	14,698	12,370	12,166	10,294

Table A.2
Controlling for Foreign Direct Investment

This table repeats the analysis of Table 6 and Table 7 but controlling for the inverse hyperbolic sine of foreign direct investment (FDI) into the U.S. at country×year level. The inverse hyperbolic sine function is used to allow for negative values. Robust standard errors in parentheses are clustered at the country-class level. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Patent Difference-in-Differences

	Log(1+Patents)					
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	0.171***	0.122***	0.178***	0.196***	0.180***	0.191***
	(0.0183)	(0.0193)	(0.0300)	(0.0343)	(0.0322)	(0.0377)
Country × Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
FDI Controls	Yes	Yes	Yes	Yes	Yes	Yes
Class Type	USPC	CPC	USPC	CPC	USPC	CPC
Treatment Type	Any	Any	Mode	Mode	Majority	Majority
R^2	0.912	0.918	0.934	0.932	0.934	0.935
Observations	38,506	33,756	14,618	12,292	12,100	10,226

Table A.2
(Continued)

Panel B: Patent Dynamics

	Log(1+Patents)					
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × 𝟙(Event Year=-5)	-0.0300	-0.0299	-0.0376	-0.0386	-0.0521	-0.0464
	(0.0225)	(0.0228)	(0.0347)	(0.0383)	(0.0389)	(0.0424)
Treated × 𝟙(Event Year=-4)	-0.0297	-0.0231	-0.0342	-0.0574	-0.0468	-0.0607
	(0.0211)	(0.0209)	(0.0339)	(0.0353)	(0.0380)	(0.0392)
Treated × 𝟙(Event Year=-3)	-0.0254	-0.0179	-0.0280	-0.0443	-0.0283	-0.0466
	(0.0191)	(0.0194)	(0.0294)	(0.0320)	(0.0325)	(0.0346)
Treated × 𝟙(Event Year=-2)	-0.0228	-0.0257	-0.00935	-0.0213	-0.0286	-0.0104
	(0.0166)	(0.0181)	(0.0260)	(0.0290)	(0.0297)	(0.0313)
Treated × 𝟙(Event Year=0)	0.0686***	0.0712***	0.0891***	0.0963***	0.0900***	0.0699**
	(0.0172)	(0.0184)	(0.0261)	(0.0291)	(0.0294)	(0.0312)
Treated × 𝟙(Event Year=1)	0.104***	0.0743***	0.140***	0.120***	0.117***	0.112***
	(0.0197)	(0.0206)	(0.0311)	(0.0338)	(0.0341)	(0.0370)
Treated × 𝟙(Event Year=2)	0.158***	0.104***	0.158***	0.168***	0.149***	0.158***
	(0.0224)	(0.0239)	(0.0340)	(0.0384)	(0.0370)	(0.0424)
Treated × 𝟙(Event Year=3)	0.175***	0.120***	0.149***	0.176***	0.151***	0.189***
	(0.0242)	(0.0251)	(0.0384)	(0.0423)	(0.0420)	(0.0459)
Treated × 𝟙(Event Year=4)	0.205***	0.115***	0.221***	0.184***	0.207***	0.189***
	(0.0259)	(0.0277)	(0.0426)	(0.0478)	(0.0468)	(0.0520)
Treated × 𝟙(Event Year=5)	0.223***	0.148***	0.217***	0.273***	0.210***	0.271***
	(0.0278)	(0.0297)	(0.0440)	(0.0511)	(0.0481)	(0.0561)
Country × Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
FDI Controls	Yes	Yes	Yes	Yes	Yes	Yes
Class Type	USPC	CPC	USPC	CPC	USPC	CPC
Treatment Type	Any	Any	Mode	Mode	Majority	Majority
R^2	0.912	0.918	0.934	0.933	0.934	0.936
Observations	38,506	33,756	14,618	12,292	12,100	10,226

Table A.2
(Continued)

Panel C: Citation Difference-in-Differences

	Log(1+Citations)					
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	0.314***	0.252***	0.318***	0.386***	0.330***	0.360***
	(0.0315)	(0.0330)	(0.0491)	(0.0557)	(0.0529)	(0.0597)
Country × Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
FDI Controls	Yes	Yes	Yes	Yes	Yes	Yes
Class Type	USPC	CPC	USPC	CPC	USPC	CPC
Treatment Type	Any	Any	Mode	Mode	Majority	Majority
R^2	0.842	0.852	0.877	0.878	0.877	0.886
Observations	38,506	33,756	14,618	12,292	12,100	10,226

Table A.2
(Continued)

Panel D: Citation Dynamics

	Log(1+Citations)					
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × 𝟙(Event Year=-5)	-0.0423	-0.0437	-0.0535	-0.0780	-0.0659	-0.102
	(0.0466)	(0.0483)	(0.0685)	(0.0754)	(0.0754)	(0.0828)
Treated × 𝟙(Event Year=-4)	-0.0569	-0.0269	-0.0587	-0.0911	-0.0832	-0.103
	(0.0464)	(0.0460)	(0.0701)	(0.0741)	(0.0787)	(0.0793)
Treated × 𝟙(Event Year=-3)	-0.0451	-0.0246	-0.0478	-0.0883	-0.0379	-0.112
	(0.0433)	(0.0430)	(0.0620)	(0.0678)	(0.0690)	(0.0727)
Treated × 𝟙(Event Year=-2)	-0.0389	-0.0195	-0.0121	-0.0441	-0.0185	-0.0342
	(0.0411)	(0.0423)	(0.0603)	(0.0651)	(0.0692)	(0.0705)
Treated × 𝟙(Event Year=0)	0.151***	0.211***	0.178***	0.249***	0.227***	0.174**
	(0.0405)	(0.0429)	(0.0615)	(0.0670)	(0.0691)	(0.0688)
Treated × 𝟙(Event Year=1)	0.218***	0.171***	0.290***	0.250***	0.257***	0.193**
	(0.0445)	(0.0460)	(0.0676)	(0.0736)	(0.0746)	(0.0802)
Treated × 𝟙(Event Year=2)	0.295***	0.214***	0.269***	0.336***	0.303***	0.303***
	(0.0480)	(0.0515)	(0.0718)	(0.0782)	(0.0783)	(0.0857)
Treated × 𝟙(Event Year=3)	0.300***	0.260***	0.243***	0.339***	0.252***	0.333***
	(0.0502)	(0.0522)	(0.0754)	(0.0820)	(0.0830)	(0.0868)
Treated × 𝟙(Event Year=4)	0.358***	0.244***	0.395***	0.329***	0.379***	0.316***
	(0.0529)	(0.0552)	(0.0846)	(0.0882)	(0.0935)	(0.0948)
Treated × 𝟙(Event Year=5)	0.396***	0.296***	0.375***	0.498***	0.350***	0.480***
	(0.0543)	(0.0584)	(0.0814)	(0.0889)	(0.0892)	(0.0957)
Country × Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
FDI Controls	Yes	Yes	Yes	Yes	Yes	Yes
Class Type	USPC	CPC	USPC	CPC	USPC	CPC
Treatment Type	Any	Any	Mode	Mode	Majority	Majority
R^2	0.842	0.852	0.877	0.879	0.877	0.886
Observations	38,506	33,756	14,618	12,292	12,100	10,226

B Matching VentureXpert with USPTO Patent Data

Name Standardization

In order to match VentureXpert with data from the USPTO, we begin by standardizing the company names in both, using the name standardization routines developed by the NBER Patent Data Project to create a bridge file to COMPUSTAT.[28] These routines standardize common company prefixes and suffixes building on a list created by Derwent World Patent Index (Thomson Reuters); they also identify a company's stem name excluding these prefixes and suffixes. Similarly, we standardize the location names from both datasets. This is done to correct spelling errors as well as other types of errors that commonly occur, particularly in the patent data. For example, in some cases, a neighborhood name is used rather than the name of a city. In other cases, country codes are listed as state codes, e.g. a patent assignee from Germany (DE) may be coded as being from Delaware (DE). The city name standardization is done by running all location names through the Google Maps API, which automatically corrects close, but inaccurate text representations of location names and returns a standardized name broken down into its component parts (city, state, country), along with latitude and longitude information.

Creating Consistent Assignee Identifiers

The USPTO data lack any kind of consistent assignee ID. Patent assignees often go by many variations of the same name on different patents, and typos are also fairly common. The NBER Patent Data Project created a consistent assignee ID, but the NBER data end in 2006. We extend and improve upon the NBER assignee ID using the following procedure: we code two patents as having the same assignee if (1) they share the same NBER assignee ID, or (2) they share the same stem name, city, and state, or (3) they share the same first four letters, city, state, inventor first name, and inventor last name, or (4) they share the same initials, city, state, inventor first name, and inventor last name, or (5) they share the same standardized full name.

The Matching Procedure

With the standardized company and city names, along with the assignee ID, we then use the following matching procedure:

1. Each standardized name associated with a company in VentureXpert is matched with standardized names from the USPTO data.[29] If an exact match is found, this is taken to be the same company and hence it is removed from the set of names that need to be matched.

[28] https://sites.google.com/site/patentdataproject/

[29] Many companies have multiple names listed in VentureXpert, reflecting the fact that young companies often change their name as they mature.

2. For the remaining companies in VentureXpert, each stem name associated with a company is matched with stem names from the USPTO data. If an exact match is found and enough other identifying information matches as well, this is taken to be the same company and it is removed from the set of names that need to be matched. If an exact match is found, but not enough other identifying information matches as well, the match is added to a list of borderline matches to be checked manually.

   (a) For a stem match to be considered definite, the standardized city/state combination also has to match, or the state has to match along with the time period (first patent application was after the company founding year).

3. For the remaining companies in VentureXpert, each stem name associated with a company is matched with up to 10 close stem names from the USPTO data using a padded bi-gram comparator. Fuzzy matches with match quality between 1.5 and 2 that also had a city/state match were kept for review, as were fuzzy matches with quality above 2 with only a state match.

4. The borderline matches identified using the above procedure were reviewed by hand, now also using other qualitative information from both data sources, including full patent abstracts, and paragraph-long company descriptions.