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

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Abstract

The treatment of foreign investors has been a contentious topic in U.S. entrepreneurship policy in recent years. This paper examines foreign corporate investments in Silicon Valley from a theoretical and empirical perspective. We model a setting where such funding may allow U.S. entrepreneurs to pursue technologies that they could not otherwise, but may also lead to spillovers to the overseas firm providing the financing and the nation where it is based. 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 investments. Using as comprehensive as possible a sample of investments by non-U.S. corporate investors in U.S. start-ups between 1976 and 2015, we find evidence consistent with the presence of knowledge spill-overs 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 four years 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. A particular concern is corporate venture investments, since these investors 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 investment in Magic Leap, Baidu's purchase of shares in Velodyne, and Lenovo and Tencent's investments in Meta, 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 as 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 invest 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 about their consequences among the U.S. venture capital community (National Venture Capital Association, 2019). In response to this debate and the new rules, anecdotal accounts suggest that investments in new ventures by Chinese-based entities dropped sharply in recent years (Somerville, 2019). Similar controversies have played out contemporaneously in, among other nations, Australia, Canada, Germany, and especially Israel (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] Nor has this been a major focus of works on trade and innovation. In Shu and

[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

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 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. In each there are a variety of industries, with one incumbent in each nation. These firms differ in their labor productivity, and engage in Bertrand competition. In each nation, start-ups may appear that are potentially more productive, 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. 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.

We posit that 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 start-ups with the potential to enhance domestic productivity may consequentially languish unfunded.

We explore the dynamics of the equilibrium in this model to differences in the relative technological positioning of the leader and follower incumbent firms. 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 probability 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. The numerical examples suggest that the optimal cost will have an inverted U shape. As the threat of military competition grows, the exercises suggests that the optimal cost imposed on

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).

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.

We then seek to explore these ideas empirically, to see whether we find evidence supportive of the model. We begin acknowledging that this analysis by necessity presents correlations rather than casual relationships. In particular, a number of papers have 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 as more as suggestive that the trade-offs illustrated in the model seem reasonable.

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. start-ups as possible. We identify transactions involving 344 companies from 32 distinct countries between 1976 and 2015. We identify the patents of the start-up 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 start-up focuses on. In a follow-on analysis, we examine citations by organizations in that nation to the patents of U.S. start-ups. These also increase in the relevant patent classes after a foreign corporate investment. The results 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. Similarly, knowledge flows appear to be greater in classes that contain patents subject to a secrecy order from the Federal government. These patterns of patenting and citations suggest the real knowledge transfer is taking place.

We then look at where these investments are more frequent. We show 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.

We finally turn to examine the consequences of these investments. While we cannot demonstrate causality, more foreign investments in firms specializing in a technology class are associated with more subsequent patenting by U.S. start-ups. 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.

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 the foreign VC investment and explicitly models the interplay between technological differences across competing firms and their incentives to invest abroad.

The plan of this paper is as follows. Part 2 lays out the theory, and the third part the numerical example. Part 4 describes the construction of the data set. The fifth part presents the results. The final section concludes the paper.

2 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 start-ups 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 start-ups 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 start-up. This new channel of foreign investment will be the focus of our analysis.

2.1 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 thecross-border investment cost, whose price is the numeraire. The final-good production technology is the following CES composite of industrial goods:

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

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:

$$Q_{Aj}(t) = \left(q_{Aj}(t)^{\alpha} + q^*_{Bj}(t)^{\alpha}\right)^{1/\alpha}. \tag{2}$$

$Q_{Bj}(t)$ 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:

$$q_{cj}(t) = z_{cj}(t)\, l_{cj}(t), \tag{3}$$

where l_{cj} denotes the amount of labor used in production by firm (c,j), and z_{cj} denotes the firm's productivity level.[3] 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 "start-up"). When there is entry during the time interval Δt, the new start-up replaces existing domestic incumbent, and the productivity level with which the new incumbent (c,j) operates becomes

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

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

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}.[4] 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.

Start-ups and Foreign Investment. Incumbent firms remain in the business until a domestic entrant (a new "start-up") 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 produces with an inferior technology in its industry. 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 thes business idea to a viable business venture.[5] In this case, there are three cases: (i) with $\bar{p}$, the entrepreneur finds financing domestically,[6] (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 gets lost unimplemented.[7]

Foreign investment into an idea happens as follows. When there is 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 $1 - \bar{p}$. 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 start-up 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 foreign incumbent, in which it has invested. These spillovers arrive at an 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

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

[5] 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.

[6] For now, we take this parameter to be common across countries. We consider relaxing this assumption in later iterations.

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

catch-up), and with probability $1-\phi$, the improvement is only one step (slow catch-up).[8] 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 start-up enters the business without receiving foreign investment. Finally, the investing firm earns a Δ share of the profits the new investee start-up generates.

Figure 1 summarizes the possibilities associated with entry in a given industry in the leader country (US 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 (following cutoff rule in equilibrium), 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:

$$U_c\left(t\right)=\int_t^\infty \exp\left(-\rho\left(\tilde{t}-t\right)\right)\ln C_c\left(\tilde{t}\right)d\tilde{t} \tag{4}$$

where $C_c\left(t\right)$ 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

$$rA_c(t)+Lw(t)=P_c(t)C_c(t)+\dot{A}_c(t)+G_c(t), \tag{5}$$

where r is the fixed 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

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

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

[8] 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 $\delta>\delta_0$.

2.2 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 $-c$).[9]

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

$$q_{cj} = \frac{p_{cj}^{\frac{1}{\alpha-1}}}{p_{cj}^{\frac{\alpha}{\alpha-1}} + \left(p^*_{-cj}\right)^{\frac{\alpha}{\alpha-1}}} Y_c \quad \text{and} \quad q^*_{-cj} = \frac{\left(p^*_{-cj}\right)^{\frac{1}{\alpha-1}}}{p_{cj}^{\frac{\alpha}{\alpha-1}} + \left(p^*_{-cj}\right)^{\frac{\alpha}{\alpha-1}}} Y_c. \tag{6}$$

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, $q^*_{cj} = q_{cj}\,(Y_{-c}/Y_c)$ 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

$$s_{cj} = \frac{p_{cj}^{\frac{\alpha}{\alpha-1}}}{p_{cj}^{\frac{\alpha}{\alpha-1}} + \left(p^*_{-cj}\right)^{\frac{\alpha}{\alpha-1}}} \quad \text{and} \quad s^*_{-cj} = \frac{\left(p^*_{-cj}\right)^{\frac{\alpha}{\alpha-1}}}{p_{cj}^{\frac{\alpha}{\alpha-1}} + \left(p^*_{-cj}\right)^{\frac{\alpha}{\alpha-1}}}. \tag{7}$$

The optimal prices follow as

$$p_{cj} = \frac{1-\alpha s_{cj}}{\alpha\,(1-s_{cj})}\frac{w(t)}{z_{cj}} \quad \text{and} \quad p^*_{-cj} = \frac{1-\alpha s^*_{-cj}}{\alpha\left(1-s^*_{-cj}\right)}\frac{w(t)}{z_{-cj}}. \tag{8}$$

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

$$\Pi_{cj} = \frac{s_{cj}\,(1-\alpha)}{1-\alpha s_{cj}} Y_c \equiv \pi_{cj} Y_c \quad \text{and} \quad \Pi^*_{-cj} = \frac{s^*_{-cj}\,(1-\alpha)}{1-\alpha s^*_{-cj}} Y_c \equiv \pi^*_{cj} Y_c. \tag{9}$$

As a consequence of unit-elastic demand at the industry level, equations (7)-(9) define firms' revenue

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

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 there is intra-industry spillovers 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}.[10] 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 ($d = 0$):

$$\begin{aligned} rV^0_{Am}(t) - \dot{V}^0_{Am}(t) = \mathbf{\Pi}_{Am}(t) - \tau^0_{Am}(t) V^0_{Am}(t) + \tau_B \left[V^0_{Am-1}(t) - V^0_{Am}(t) \right] \\ + \delta_0 \phi \left[V^0_{A0}(t) - V^0_{Am}(t) \right] + \delta_0 (1 - \phi) \left[V^0_{Am-1}(t) - V^0_{Am}(t) \right]. \end{aligned} \tag{10}$$

Let us dissect equation (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 start-up with necessary financing, the incumbent exits the business, destroying the value of the incumbent firm. The probability of a successful firm depends on foreign investment decision of foreign firms 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

[10] 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:

$$\begin{aligned} rV^0_{Am}(t)-\dot{V}^0_{Am}(t) = {} & \mathbf{\Pi}_{Am}(t)-\tau_A V^0_{Am}(t)+\delta_0\phi\left[V^0_{A0}(t)-V^0_{Am}(t)\right] \\ & +\delta(1-\phi)\left[V^0_{Am-1}(t)-V^0_{Am}(t)\right] \\ & +\tau_B\bar{p}\left[V^0_{Am-1}(t)-V^0_{Am}(t)\right] \\ & +\tau_B\left(1-\bar{p}\right)\int_0^{u_\varepsilon}\max_{\kappa\in\{0,1\}}\kappa\left[V^1_{Am-1}(t)-V^0_{Am}(t)-\varepsilon Y(t)\right]d\varepsilon, \end{aligned} \tag{11}$$

where $Y(t)$ denotes final output. Again, the first two components on the right-hand side are profits and the effect and 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 (11) describes what happens when the firm gets the chance to invest in the foreign start-up, which happens 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 start-up 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 remain the same, as the foreign business idea is not implemented due to 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 start-up 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

$$\kappa^0(m)=\begin{cases} 1 & if \quad \varepsilon<\bar{\varepsilon}^0(m) \\ 0 & if \quad \varepsilon>\bar{\varepsilon}^0(m) \end{cases}. \tag{12}$$

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

$$rV^1_{Am}(t) - \dot{V}^1_{Am}(t) = (1-\Delta)\mathbf{\Pi}_{Am}(t) - \tau^1_{Am}(t)V^1_{Am}(t) + \tau_B\left[V^1_{Am-1}(t) - V^1_{Am}(t)\right] + \delta\phi\left[V^0_{A0}(t) - V^1_{Am}(t)\right] + \delta(1-\phi)\left[V^1_{Am-1}(t) - V^1_{Am}(t)\right]. \tag{13}$$

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:

$$\begin{aligned} rV^1_{Am}(t) - \dot{V}^1_{Am}(t) = {} & \mathbf{\Pi}_{Am}(t) + \Delta\mathbf{\Pi}_{Bm}(t) - \tau_A V^1_{Am}(t) \\ & + \delta(1-\phi)\left[V^0_{A0}(t) - V^1_{Am}(t)\right] + \delta\phi\left[V^1_{Am-1}(t) - V^1_{Am}(t)\right] \\ & + \tau_B\bar{p}\left[V^0_{Am-1}(t) - V^1_{Am}(t)\right] \\ & + \tau_B(1-\bar{p})\int_0^{u_\varepsilon}\max_{\kappa\in\{0,1\}}\kappa\left[V^1_{Am-1}(t) - V^1_{Am}(t) - \varepsilon Y(t)\right]d\varepsilon, \end{aligned} \tag{14}$$

Notice that this laggard receives the Δ fraction of the profits the industry leader generates, as that leader firm had emerged upon 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 emerging startup would generate. The cutoff rule is defined reciprocally as in equation 12:

$$\kappa^0(m) = \begin{cases} 1 & if \quad \varepsilon < \bar{\varepsilon}^1(m) \\ 0 & if \quad \varepsilon > \bar{\varepsilon}^1(m) \end{cases}, \tag{15}$$

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

$$rV^0_{A0}(t) - \dot{V}^0_{A0}(t) = \mathbf{\Pi}_{A0}(t) - \tau_A V^0_{A0}(t) + \tau_B\left[V^0_{A-1}(t) - V^0_{A0}(t)\right]. \tag{16}$$

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

$$\frac{rV(t) - \dot{V}(t)}{Y(t)} = rv(t) - (\dot{v}(t) + g(t)v(t)) = (r - g(t))\,v(t) - \dot{v}(t), \tag{17}$$

where $g(t) = \dot{Y}(t)/Y(t)$ denotes the growth rate of global consumption. Then, the normalized value function of a leader firm in a low-spillover state becomes, for example:

$$(r - g(t))\, v^0_{Am}(t) - \dot{v}^0_{Am}(t) = 2\pi_{Am}(t) - \tau^0_{Am}(t) v^0_{Am}(t) + \tau_B \left[v^0_{Am-1}(t) - v^0_{Am}(t)\right] + \delta_0 \phi \left[v^0_{A0}(t) - v^0_{Am}(t)\right] + \delta_0 (1-\phi) \left[v^0_{Am-1}(t) - v^0_{Am}(t)\right]. \quad (18)$$

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

$$(r - g)\, v^0_{Am} = 2\pi_{Am} - \tau^0_{Am} v^0_{Am} + \tau_B \left[v^0_{Am-1} - v^0_{Am}\right] + \delta_0 \phi \left[v^0_{A0} - v^0_{Am}\right] + \delta_0 (1-\phi) \left[v^0_{Am-1} - v^0_{Am}\right]. \quad (19)$$

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

$$\begin{aligned}(r - g)\, v^0_{Am} &= 2\pi_{Am} - \tau_A v^0_{Am} + \delta_0 \phi \left[v^0_{A0} - v^0_{Am}\right] + \delta (1-\phi) \left[v^0_{Am-1} - v^0_{Am}\right] \\ &\quad + \tau_B \bar{p} \left[v^0_{Am-1} - v^0_{Am}\right] \\ &\quad + \tau_B (1 - \bar{p}) \Pr\left[\varepsilon < \bar{\varepsilon}^0(m)\right] \times \left\{\left[v^1_{Am-1} - v^0_{Am}\right] - \mathbb{E}\left[\varepsilon | \varepsilon < \bar{\varepsilon}^0(m)\right]\right\} \\ &= 2\pi_{Am} - \tau_A v^0_{Am} + \delta_0 \phi \left[v^0_{A0} - v^0_{Am}\right] + \delta (1-\phi) \left[v^0_{Am-1} - v^0_{Am}\right] \\ &\quad + \tau_B \bar{p} \left[v^0_{Am-1} - v^0_{Am}\right] + \tau_B (1 - \bar{p}) \frac{\left[v^1_{Am-1} - v^0_{Am}\right]^2}{u_\varepsilon}. \end{aligned} \quad (20)$$

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.

2.3 Model Discussion

The model presents a rich setting that captures the essence of foreign VC investment highlighted in the empirical section. A foreign VC investment in the model benefits the investor in both pecuniary (additional profits) and non-pecuniary (spillovers) ways. Reflecting on the findings presented in Section 5.1, investing firms increase their patenting (measured by higher δ) after an investment.

The model also provides a useful framework to investigate the determinants of the foreign VC investment, discussed in Section 5.2. 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 VC 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 VC 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.

3 Numerical Example

To illustrate the key implications of our framework, we now present a what we term 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.

3.1 Parameters

In the numerical exercise, we assume symmetric countries 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 VC investment and subsequent innovative activity of firms, we discipline most parameters using statistics from our sample used in the empirical section and the USPTO patent database. The parameter values are summarized in Table 1.

External Parameters. We set the subjective rate of time preference of the household (rho) 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) in a proportion that reflects 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.[11]

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.[12] 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.[13] 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 among all foreign patents. This ratio gives the rate with which foreign firms produce their most influential patents, and we assume that, in our model, the share of drastic improvements in spillovers that foreign firms receive captures the share of top five percent of mostly cited foreign patents. We assume that a VC-backed start-up and the investor share the profits generated by the start-up equally. Unfortunately, we do not have a convincing empirical measure of the profit

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

[12] In Table 3, 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 3 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.

[13] 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.

share held by the investor. Therefore, we 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.[14]

Internal Parameters. 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, these parameters 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 registered a patent, and (iv) the fraction of foreign VC investment in total VC investment received by patenting firms observed in our sample.[15] To be precise, the denominator in the last ratio reflects the investment in domestic startups by both foreign and domestic investors, which happens at rate $\bar{p}$. 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, and the calibrated value 1.058 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 two varieties in an industry and, thus, the profits firms can charge given their technological advancement relative to their rival. The final two parameters determine VC investment by domestic and foreign investors. The investment cost upper bound (u_ε), which is symmetric for both countries in the calibrated model, affects the average cost a firm faces when investing in foreign firms and, hence, the prevalence of foreign VC investment in the host country.[16] To discipline this parameter, we

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

[15] The first two targets are computed from the BEA database, and the other two are computed from the micro-level data described in the next section. All targets are averages between 1976 and 2015.

[16] See Section 3.3 for how we model the change in this cost parameter as a result of country-specific policy.

include in the set of targets the fraction of foreign VC investment in total VC investment received by patenting firms in the United States observed in our sample, which is about 63 percent. Finally, given u_ε—the parameter that shapes foreign VC investment in the model—the share of patenting U.S. firms that receive any VC investment (domestic or foreign) informs the calibration about the probability of receiving domestic financing ($\bar{p}$). The value of this moment in our data sample is about 25 percent. The calibrated model hits these moments exactly, as summarized in Table 2.

3.2 Taking Stock

Now we turn to the illustration of the key implications of the model. First, the model captures the insight from Section 5.1—the patenting intensity of foreign firms rises after VC investment—because the rate of spillover arrival increases with investment ($\delta > \delta_0$). Next, Figure 2a shows the investment decisions of firms from country B—which denotes the foreign countries—in the balanced growth path. The red line represents the probability for laggards in low-spillover state and the blue dashed line pertains to the laggards in high-spillover state. For the sake of clarity, we present the figure for laggards up to 15 steps (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 discussed in Section 5.2—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 VC 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 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 other 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.

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

3.3 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 VC 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 CVC investment poses an economic security threat to the recipient country that is increasing in the number of foreign investors.[17] We model this security cost in terms of domestic output using the following functional form:

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

where Ω_{-c1} denotes the measure of foreign firms that have investment 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.[18]

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

[17] These threats are acknowledged even by those outside the defense community: see, for instance, National Venture Capital Association (NVCA) Comments on Proposed Rule RIN 1505-AC64.

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

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 CVC 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 3.1, 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.[19] 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 in a wide range in the alternative economies and declines notably (relative to the benchmark economy) 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 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.

4 Data

In this section we describe the data that we use for our empirical analysis.

4.1 Sources

We obtain data on VC investments from the Refinitiv VentureXpert database (formerly called Thomson Reuters VentureXpert and Venture Economics). VentureXpert, along with Dow Jones' 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

[19] 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.

to be more comprehensive in terms of investment coverage, which is important for our purposes.[20] 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 corporate VC (CVC) firms, along with the countries that their ultimate parents are located in.[21] 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 U.S. Patent and Trademark Office (USPTO). While we only observe patents granted in the U.S., foreign innovators typically apply for patents in the U.S. on important inventions because it is a large market. The USPTO data cover all utility patents granted from 1976 to 2017.[22] Among other things, the data provide information on the date a patent was applied for and ultimately granted, as well as its detailed technology class. If a patent was assigned to one or more companies ("assignees"), the data also provide information on assignee name(s)/location(s). 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 30% of VC-backed companies in VentureXpert are also patent assignees in the USPTO data. Approximately 50% of VC financing rounds in VentureXpert are associated with companies that are also patent assignees in the USPTO data.

[20] 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).

[21] 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).

[22] In addition to utility patents, there are three other minor patent categories: design, reissue, and plant patents. Following the literature, we focus only on utility patents, which represent approximately 99% of all awards (Jaffe and Trajtenberg (2002)).

4.2 Key Variables and Summary Statistics

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

4.2.1 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. Patents with assignees from multiple countries are attributed equally to all of the countries of the assignees. We define a patent's class based on its primary (three-digit) USPC classification.[23] 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.

4.2.2 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 to U.S. startups as a way of measuring knowledge flows from U.S. startups to foreign entities. Citations are measured through the end of 2017.

4.2.3 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 a majority or mode of its patent applications in class c as of the time of investment in year t. For some analyses we also use a different version of this variable based on whether the startup had any patent applications in class c, rather than requiring a majority.

[23] The U.S. switched to classifying patents using the Combined Patent Classification (CPC) scheme at the start of 2015. After that point, we impute USPC classes based on the modal USPC class associated with a CPC class historically. The historical data linking USPC classes to CPC classes come from the CPC Master Classification File for U.S. Patent Grants, maintained by the USPTO.

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 invested \$100M in that startup in year t, we would define it as having invested \$20M in class A, 30M in class B, and 50M 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.

4.2.4 Basicness of a technology class

In order to distinguish basic innovation fields from applied innovation fields, 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 (2019) and include patents submitted between 1926-2018.

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 primary USPC classes into two groups: patent classes with number of backward academic citations above the year-specific median and the other not. We call the former "High Basicness" patent classes and the lower "Low Basicness" patent classes.

4.2.5 Secrecy of a technology class

To determine whether patents were subject to secrecy orders, we follow the methodology suggested by de Rassenfosse et al. (2020). From the USPTO's PAIR database (https://www.uspto.gov/learning-and-resources/electronic-data-products/patent-examination-research-dataset-public-pair), we focus on patent applications where secrecy orders were imposed (code L132) between 1951 and 2016. We match the applications to the resulting patents through the ApplicationID-PublicationID bridge file in PatentsView.

We then divide the primary USPC classes into two year-specific groups: one with any patents subject to secrecy orders with a primary assignment to that class in a given year and the other not. On average, there are 26 patent classes in the secrecy category and 403 in the non-secrecy one.

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

Another variable we are interested in 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:

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

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

4.3 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%).[24]

To put our analysis in a 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. The last two panels show that this increase was both due to an increase in CVC investment more generally during that time period (Panel B) and also an increase in the share of CVC investment made by foreign corporations (Panel C).

Next, we examine the association between foreign CVC investment and startup activity in the U.S. Since young, innovative firms are often financially constrained, we might expect that foreign CVC investment would help stimulate startup activity. Figure 6 shows the evolution of foreign CVC investment together with the number of U.S. startups raising a round of VC funding. Panel A shows the number of startups raising their first round of VC funding, while Panel B shows the number of startups raising any round. As can be seen, these two variables are significantly positively correlated (Panel A: ρ =.76; Panel B: ρ =.89). While we are cautious not to impose a causal interpretation on Figure 6, the positive correlation between foreign CVC investment and U.S. startup activity suggests that foreign CVCs do not merely crowd out other VC investors without

[24] If we compiles a similar list of the top foreign countries from 1976 to 2017, China is in second place with 10.7%.

increasing startup activity; rather, foreign CVCs appear to facilitate the funding of startups that would not have otherwise been funded.

5 Empirical Analysis

5.1 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 begin our empirical analyses by looking 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. 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.

To address such endogeneity concerns as well as possible, we use a difference-in-difference 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 U.S. startup patents in the class.

More precisely, for each treated class and potential control class, we compute the squared percentage difference in the number of patents the country produced in the two classes during the five years prior to investment. We also do the same with the number of citation the country made to U.S. startup patents in the two classes. Finally, we take the square-root of each of these and average them. Our matched control class is the one that minimizes this measure of distance between the two classes.

5.1.1 Changes in patenting activity around U.S. startup investments

Having defined treatment and control classes for a country, we begin by estimating difference-in-difference specifications of the form:

$$Patents_{fct} = \beta_1 Post_{fct} + \beta_2 Post_{fct} \times Treated_{fc} + \alpha_{fc} + \eta_t + \varepsilon_{fcd}, \tag{21}$$

where observations are a 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. In columns 1 and 2, we classify a country 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 a majority of its (eventually granted) patent applications in that class at the time of investment. 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 treatment-control pair level.

The results are reported in Table 5. In column 1, we find that after investing in a U.S. startup specializing in particular technology class, countries increase their patenting in that class by 5.6 patents per year, with the estimated effect significant at the 5% level. This represents a 43.1% increase in patenting relative to the 13 patents per year that the average foreign country produces in a technology class prior to investing in it through a startup.[25] Thus, the magnitudes are economically significant as well. In column 2, we control for year fixed effects to address the possibility that patenting in treatment classes increases relative to control classes in certain years. Our estimates remain similar with these controls. Finally, in columns 3–4, we repeat the analysis of columns 1–2, but now classify a country 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 the mode of its (eventually granted) patent applications in that class at the time of investment. As can be seen, the results remain similar. Overall, the results in Table 5 suggest that other countries do learn from U.S. startup investments, and that their own patenting begins to resemble that of the startups they invest in.

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 event-study specifications of the form:

$$\begin{aligned} Patents_{fct} = &\sum_{\tau=-5}^{5} \delta_\tau \mathbb{1}\{EventYear_{fct} = \tau\} + \\ &\sum_{\tau=-5}^{5} \beta_\tau \mathbb{1}\{EventYear_{fct} = \tau\} \times Treated_{fc} + \alpha_{fc} + \eta_t + \varepsilon_{fct} \end{aligned} \tag{22}$$

Equation 22 is the same as equation 21, 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

[25] The average number of annual patent applications submitted by a foreign country in a given patent class before the investment event is 50.63 if we focus on *the treated group* only.

to investment ($EventYear_{fct} = -1$). Table 6 and Figure 7 show the results, with Figure 7 corresponding to column (1) of Table 6. The coefficients on the interaction terms represent the difference between the treatment and control classes in each 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.

5.1.2 Changes in citation patterns around U.S. startup investments

If a country learns about a technology class from investing in a U.S. startup specializing in that class, we might not only expect the country to patent in that class more, but also to cite the patents of U.S. startups in that class more. To investigate this, we repeat the analysis of Section 5.1.1, but with the the outcome being citations to U.S. startup patents in a technology class.

Table 7, which is modeled on Table 5, shows our difference-in-difference analysis with this outcome variable. We find that countries increase their citations to U.S. startup patents in a technology class after investing in a U.S. startup that innovates in that class. In terms of magnitudes, Table 7 (column 1) implies that after investing, countries increase their relevant citations by 0.35 citation per year. This represents a 14.7% increase in citations relative to the 2.38 citations per year that the average foreign country makes to U.S. startup patents in a class prior to investing. Table 8 and Figure 8 show the full dynamics.

5.2 Heterogeneity in learning from investments in U.S. startups

As posited in the theoretical analysis, the basicness of a sector may also affect the extent of learning from a foreign VC 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 basic research conducted at the frontier. In these settings, corporate venture investments may be more critical to learning.

To test this idea, we divide the patent classes into those where the classes are above and below the median when it comes to basicness, defined (as explained in Section 4.2.4) by the backward academic citations from the patents in the class. In Table 9, we repeat several key regressions in Tables 5 and 7, now dividing observations by whether they are of patents with a primary assignment to a patent class above or below the median on the basicness measure.

As Panel A reports, the interactions between the post and treated dummies are significantly positive for patent classes with high basicness. For classes with low basicness, however, the coefficients on the interaction term are insignificant and even negative. Note that the difference in these

coefficients between high- and low-basic groups is statistically significant. When we look at citations in Panel B, we also find larger effects in patent classes with high basicness. While the differences in theses coefficients are not quite statistically significant, the point estimates go in the direction we would expect.[26] Overall, these results are consistent with the idea that there is greater cross-border learning in more basic technologies. We repeat this analysis dividing patent classes into two groups by patent originality score as defined in Hall et al. (2001). The findings also suggest that foreign investments in patent classes with high originality generate more learning spillovers than investments in those with low patent originality.[27]

Similar to how we might expect greater learning in more basic patent classes, we might also expect greater learning in more secretive classes. As described in Section 4.2.5, we define a patent class to be secretive if it contains any patents subject to secrecy orders by the U.S. government. We then repeat the analysis of Table 9, splitting our sample by patent class secrecy rather than basicness. The results are shown in Table 10. Consistent with what we would expect, we estimate stronger effects in secretive patent classes. As in the case of basicness, the difference in the estimated effects across the two types of patent classes is statistically significant for patent applications, but not quite statistically significant for citations. Overall, however, our findings suggest that foreign countries learn more from investments in U.S. startups when those startups specialize in more secretive technologies.

5.3 Determinants of cross-border startup investments

Thus far, we have shown evidence that foreign entities learn from investments in U.S. startups. Next, we explore the determinants of such 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:

$$Investment_{fct} = \alpha_0 + \beta RelativeKnowledge_{fct} + \gamma_f + \eta_t + \varepsilon_{fct}, \tag{23}$$

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 4.2.6 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 11. 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

[26] Another proxy of class basicness that we looked into is presence of top-100 universities among the assignees of patents in the class. The results are qualitatively similar if we focus on observations before 1995, but are ambiguous for more recent observations.

[27] Results are available upon request.

of a technology class relative to the U.S., it also becomes less likely to invest in a U.S. startups 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 was allocated to class c. We find qualitatively similar results using this continuous measure as well. Overall, these results suggest that foreign countries tend to invest in U.S. startups that specialize in technological areas where they are behind the U.S.

5.4 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, 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 investments in a technology class through U.S. startups and patenting in that technology class by U.S. startups.

Specifically, we estimate equations of the form:

$$StartupActivity_{c,t} = \alpha + \beta ForeignInvestment_{c,t} + \varphi_c + \eta_t + \varepsilon_{ct}, \tag{24}$$

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 12. 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. 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. startup patents in class c in year t. We again examine first patents by new patenting entities only and then those by all startups. As can be seen, we do find a positive correlation between foreign investments in a technology class through U.S. startups 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 would not otherwise be able 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

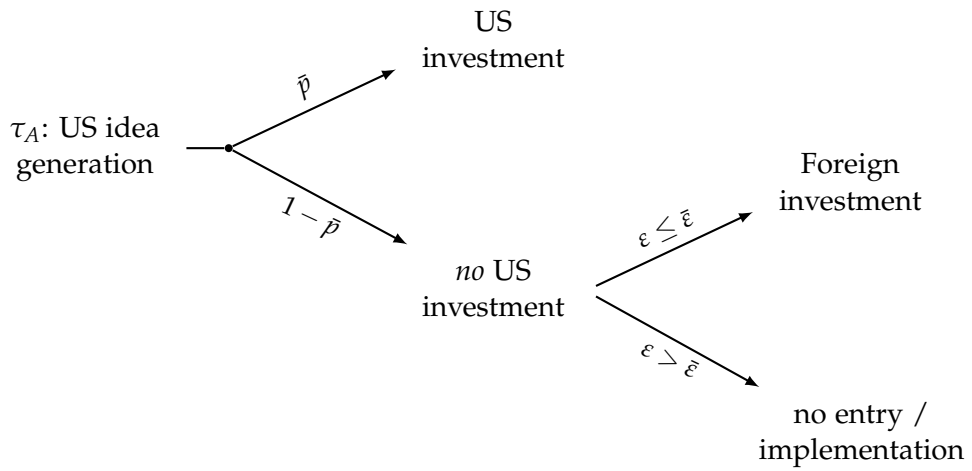
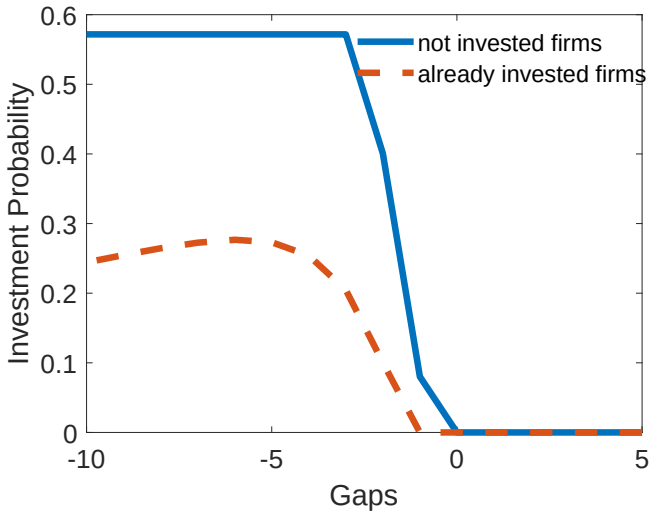


Figure 2

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)**

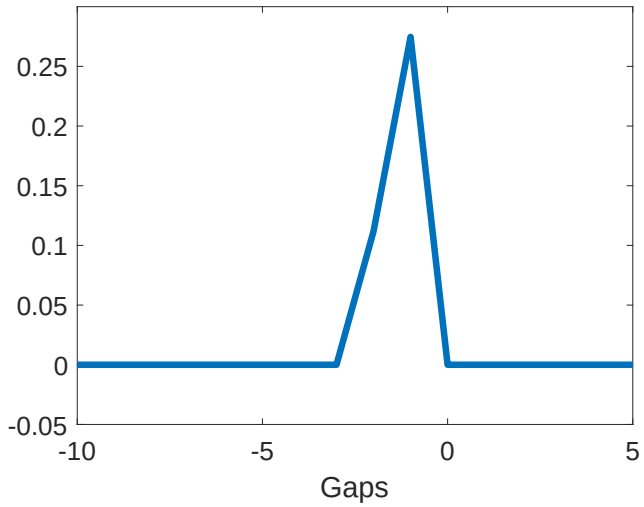
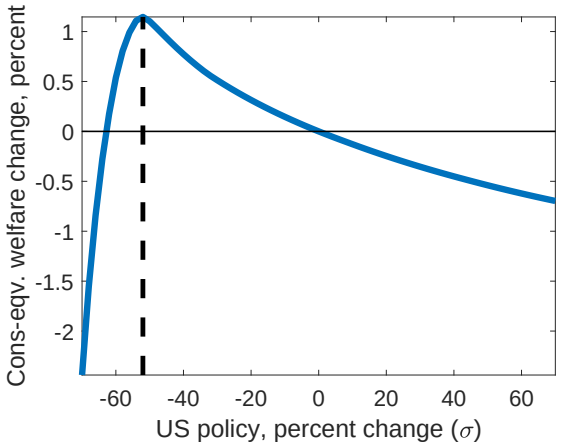
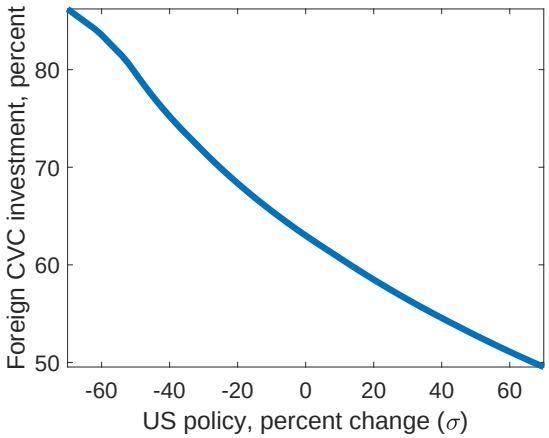


Figure 3
Policy Analysis

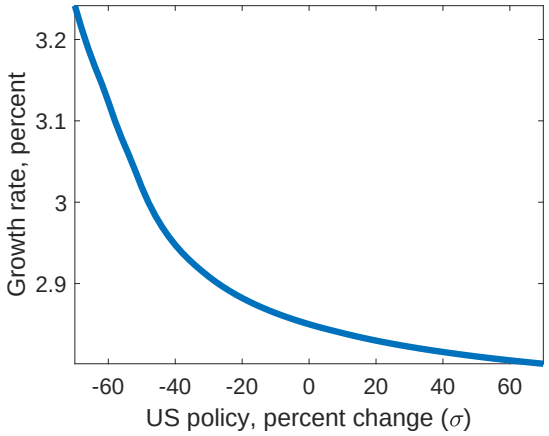
(a) **CEQ welfare**



(b) **Foreign CVC share**



(c) **Growth**



(d) **Security cost**

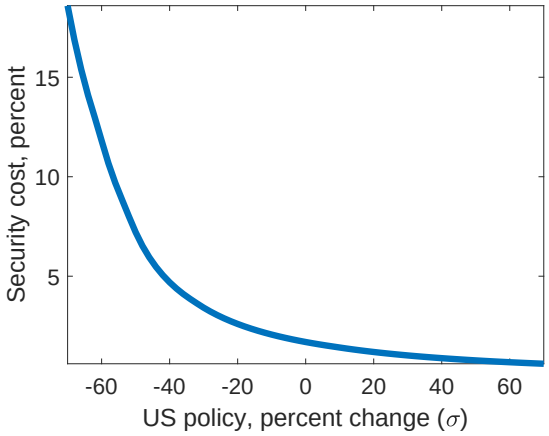
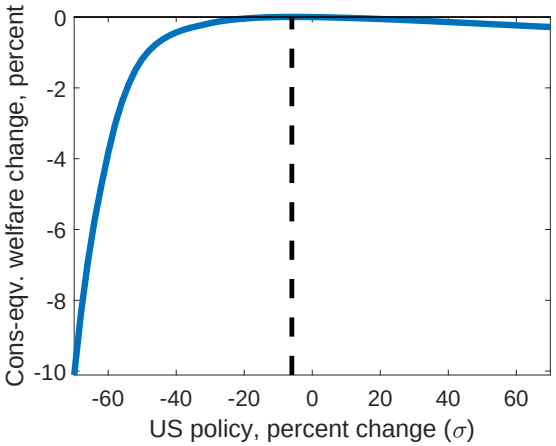
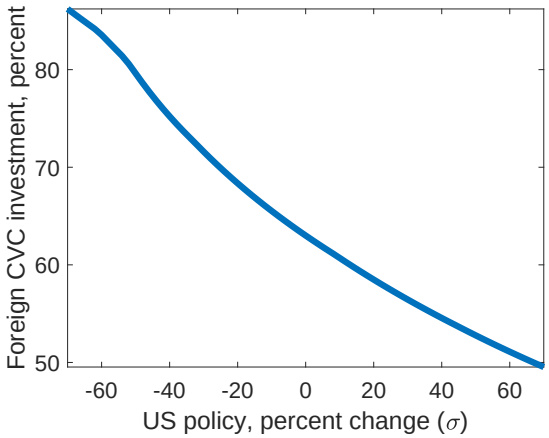


Figure 4
Policy Analysis with Higher Cost of Security

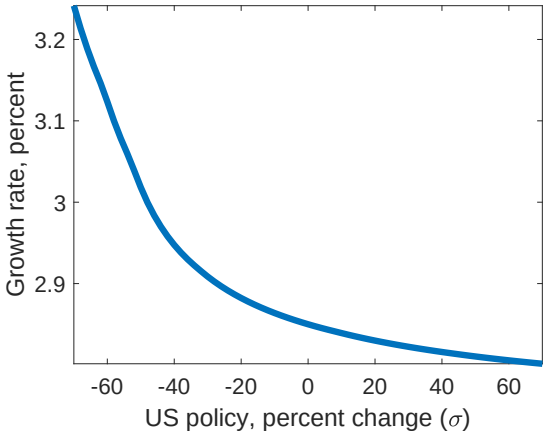
(a) **CEQ welfare**



(b) **Foreign CVC share**



(c) **Growth**



(d) **Security cost**

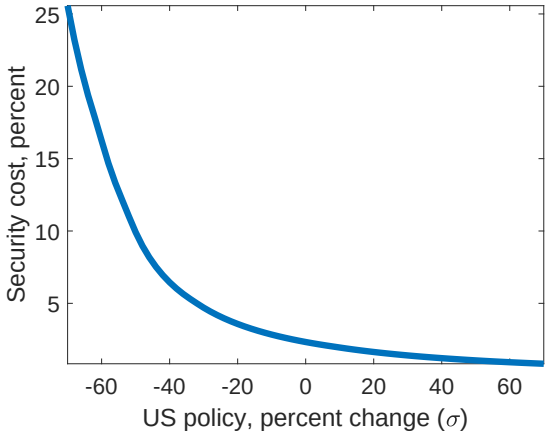


Figure 5
Corporate VC Investment Share

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

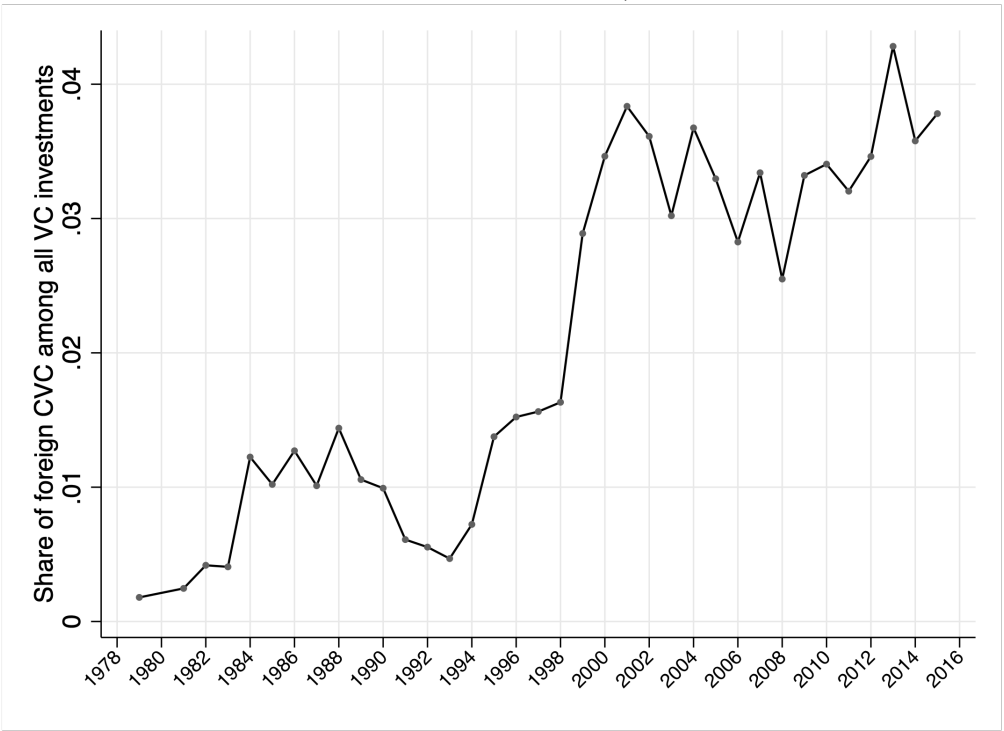
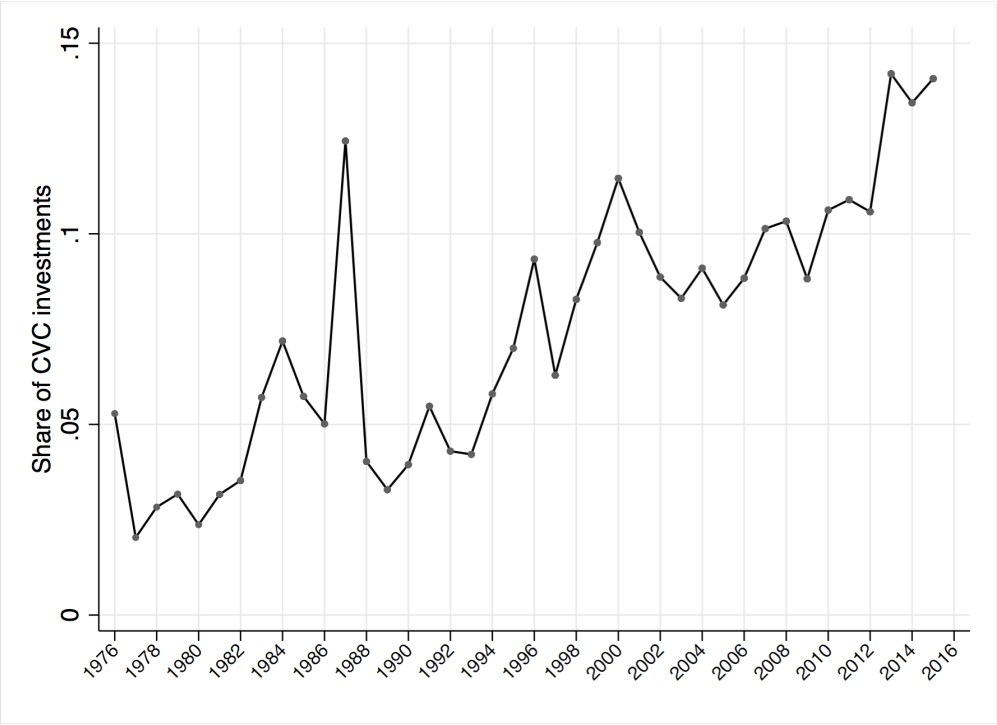


Figure 5
(Continued}
Panel B: CVC Investment / VC Investment



Panel C: Foreign CVC Investment / CVC Investment

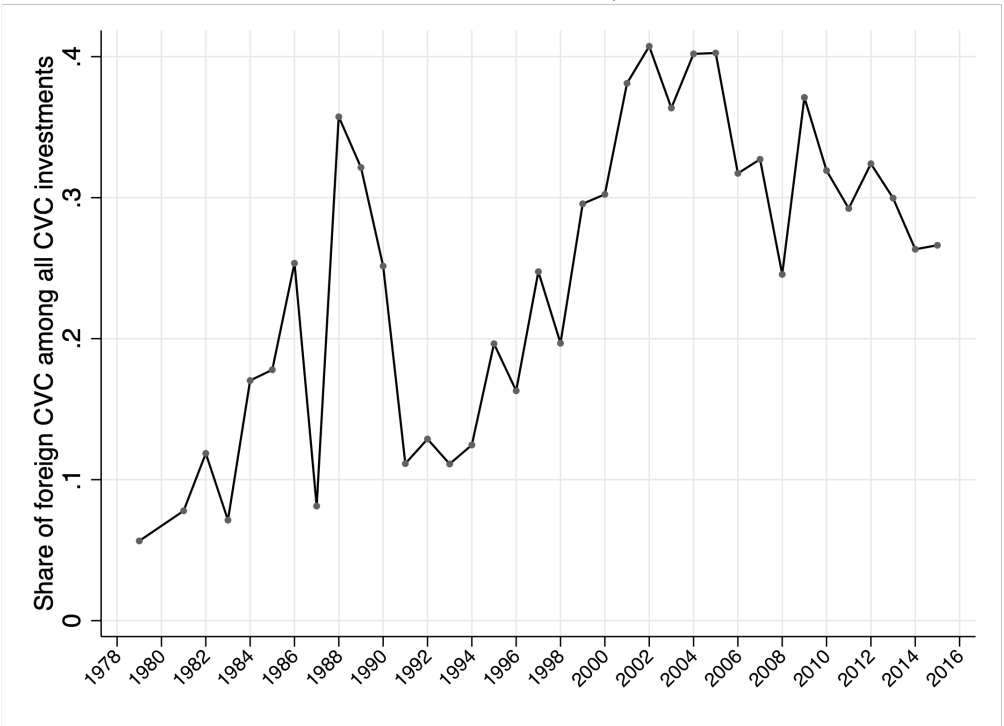
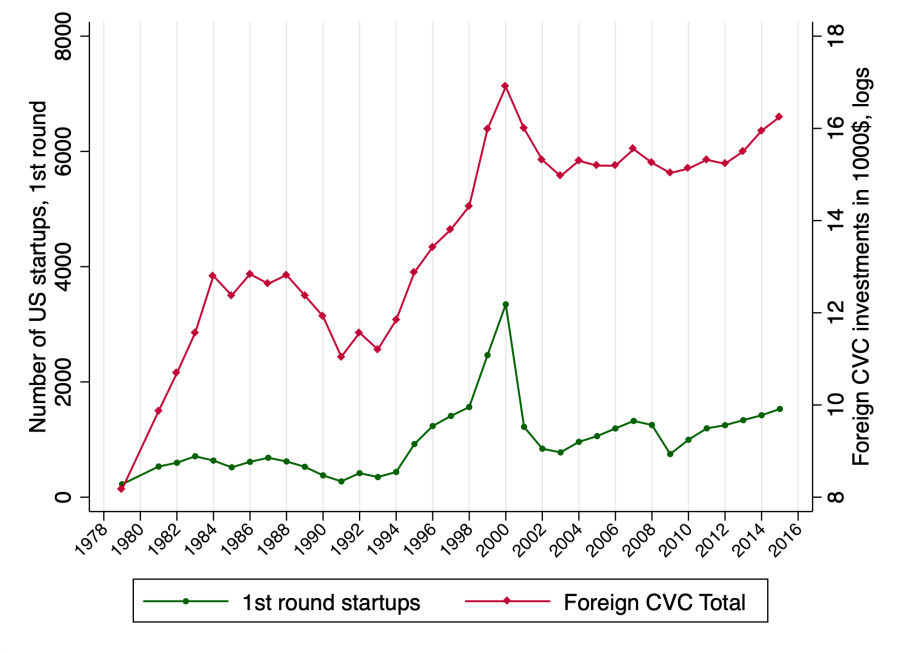


Figure 6
Foreign CVC Investment and U.S. Startup Activity

Panel A: Foreign CVC Investment and Startups Raising First Round of Investment



Panel B: Foreign CVC Investment and Startups Raising Any Round of Investment

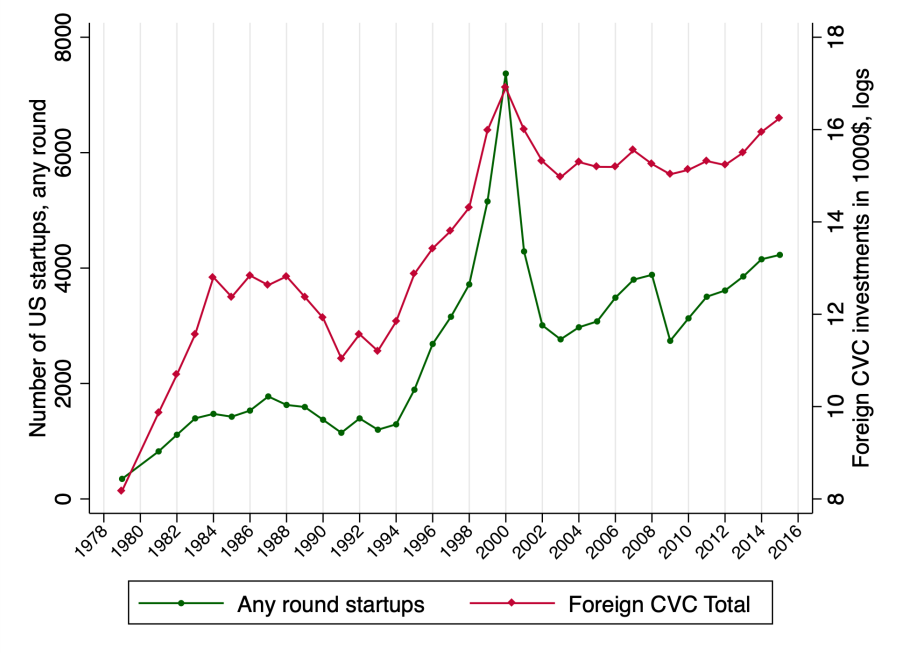


Figure 7
Dynamics: Patents

This figure shows the results of the event study according to specification (2) of Table 6. Omitted category is the year before the investment event. The vertical axes plots the differential effect of investment event on treated classes in comparison to control classes captured by coefficients $\beta_{gap}\mathbb{1}\{d = gap\} \times Treated_{fc}$.

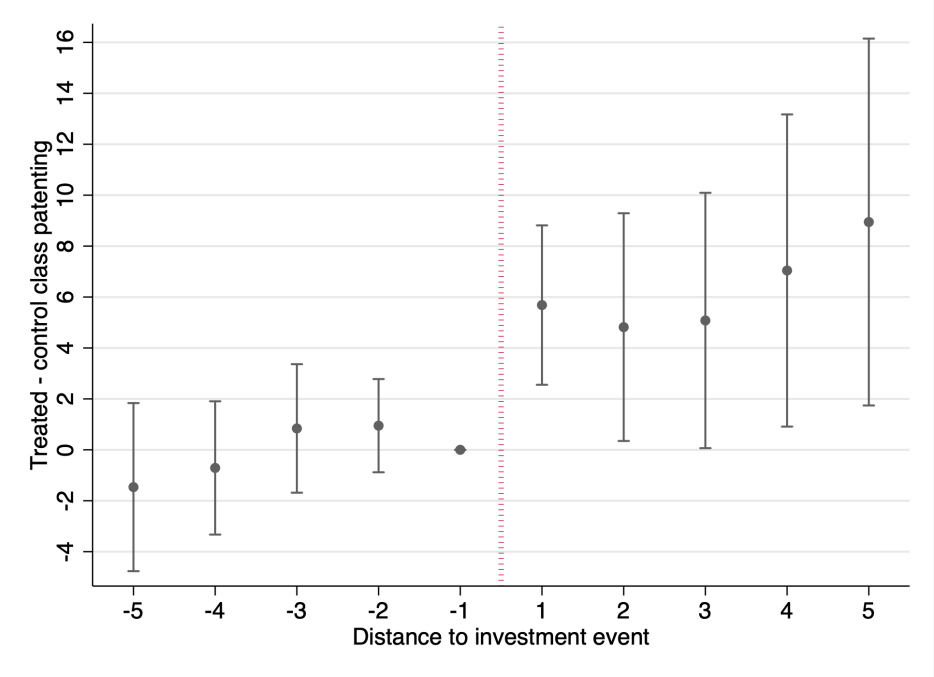


Figure 8
Dynamics: Citations

The results of the event study according to specification (2) of Table 8. Vertical axes plots the differential effect of investment event on treated classes in comparison to control classes captured by coefficients $\beta_{gap}\mathbb{1}\{d = gap\} \times Treated_{fc}$. Omitted category is the year before the investment event.

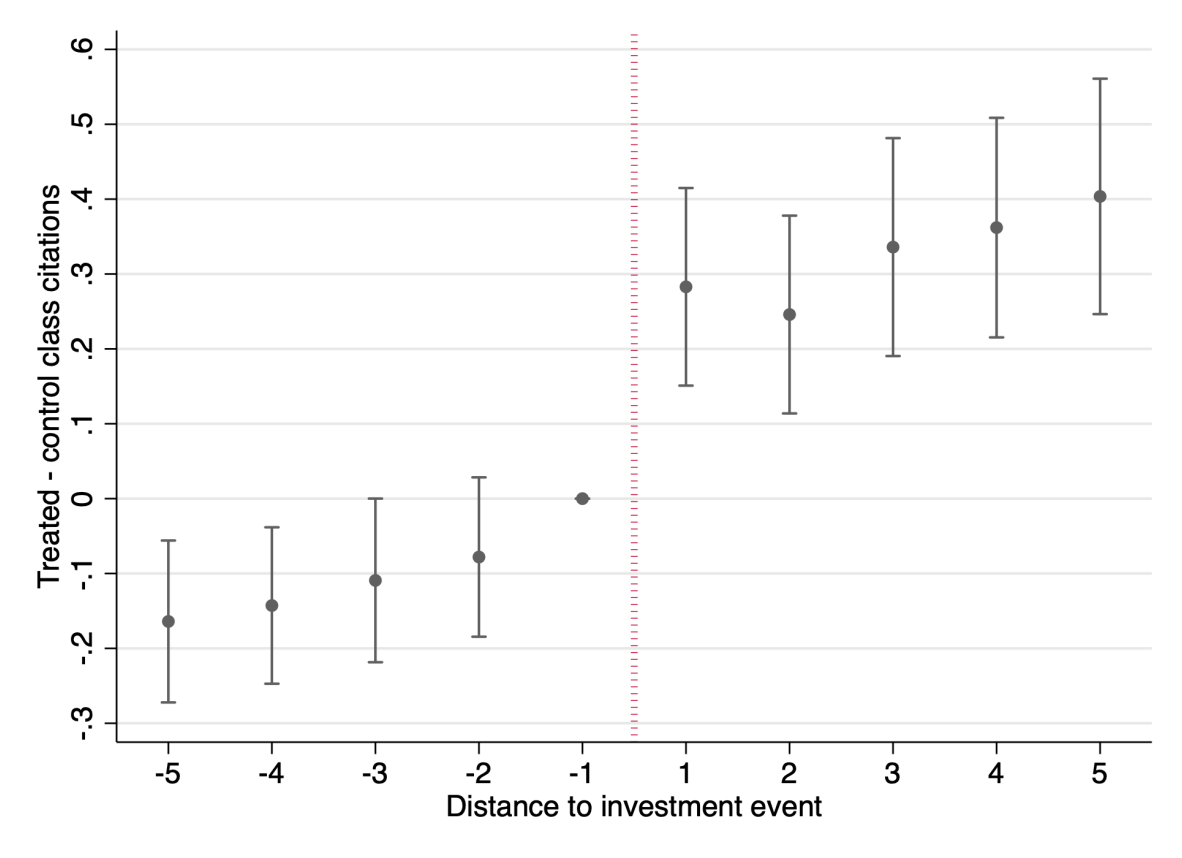


Table 1
Parameter Values

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

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

	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 4.2. Observations are at the country×patent-class×year level. Summary statistics for investment measures is 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
Annual citations to U.S. startup patents in class by foreign country	2.38	1.66	2
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
Difference-in-Difference: Patents

This table examines how a foreign country's patenting in a technology class 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 a country's first investment 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 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 U.S. startup patents in the class. 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 a majority (columns 1–2) or mode (columns 3–4) of its eventually-granted patent applications in that class at the time of investment. The variable $Patents_{fct}$ represents the number of patents country f applied for 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. Standard errors are clustered at the treatment-control pair level. *** p<0.01, ** p<0.05, * p<0.1.

	Patent applications			
	(1)	(2)	(3)	(4)
Post	8.096***	8.268***	8.068***	8.084***
	(1.653)	(1.669)	(1.558)	(1.569)
Post×Treated	5.631**	5.460**	4.859**	4.843**
	(2.349)	(2.358)	(1.888)	(1.895)
Country×Class FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Treatment Definition	Majority of startup patents in class c		Mode of startup patents in class c	
R-squared	0.857	0.884	0.821	0.855
Observations	14,310	14,310	15,764	15,764

Table 6
Dynamics: Patents

This table repeats the analysis of Table 5, 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.

	Patent Applications			
	(1)	(2)	(3)	(4)
𝟙{Event Year = -5}× Treated	-1.464	-1.464	-0.145	-0.145
	(1.677)	(1.681)	(1.641)	(1.645)
𝟙{Event Year = -4}× Treated	-0.711	-0.711	0.298	0.298
	(1.329)	(1.333)	(1.432)	(1.435)
𝟙{Event Year = -3}× Treated	0.840	0.840	0.773	0.773
	(1.282)	(1.285)	(1.271)	(1.274)
𝟙{Event Year = -2}× Treated	0.949	.949	0.810	0.810
	(0.861)	(0.932)	(0.959)	(0.961)
𝟙{Event Year = 0}× Treated	2.014	2.014	1.226	1.226
	(1.317)	(1.320)	(1.068)	(1.070)
𝟙{Event Year = 1}× Treated	5.684***	5.684***	4.269***	4.269***
	(1.590)	(1.594)	(1.286)	(1.289)
𝟙{Event Year = 2}× Treated	4.818**	4.818**	4.976***	4.976***
	(2.272)	(2.277)	(1.798)	(1.803)
𝟙{Event Year = 3}× Treated	5.079**	5.079**	5.359**	5.359**
	(2.547)	(2.554)	(2.140)	(2.145)
𝟙{Event Year = 4}× Treated	7.042**	7.042**	7.477***	7.477***
	(3.114)	(3.122)	(2.714)	(2.720)
𝟙{Event Year = 5}× Treated	8.945**	8.945**	9.366***	9.366***
	(3.660)	(3.669)	(3.154)	(3.162)
Country×Class FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Treatment Definition	Majority of startup patents in class c		Mode of startup patents in class c	
R-squared	0.688	0.688	0.622	0.622
Observations	14,310	14,310	15,764	15,764

Table 7
Difference-in-Difference: Citations

This table examines how a foreign country's patent citations to a technology class 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 a country's first investment in a U.S. startup specializing in a particular technology class. The dependent variable is the number of citations to patents of U.S. start-ups in the technology class made in patents filed in the year by entities in the foreign nation. Changes in the country's innovative activity in that "treated" technology class are compared to to changes in the same country's innovative activity in a similar "control" technology class, which 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 U.S. startup patents in the class. 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 a majority (columns 1–2) or mode (columns 3–4) of its eventually-granted patent applications in that class at the time of investment. The variable $Citations_{fct}$ represents the number of citations by country f's patents to U.S. startup 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. Standard errors are clustered at the treatment-control pair level. *** p<0.01, ** p<0.05, * p<0.1.

	Citations to U.S. Startup Patents			
	(1)	(2)	(3)	(4)
Post	-0.137***	-0.162***	-0.081*	-.113**
	(0.046)	(0.046)	(0.043)	(0.044)
Post×Treated	0.352***	0.376***	0.322***	0.364***
	(0.045)	(0.045)	(0.044)	(.043)
Country×Class FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Treatment Definition	Majority of startup patents in class c		Mode of startup patents in class c	
R-squared	0.772	0.778	0.761	0.771
Observations	14,310	14,310	15,764	15,764

Table 8
Dynamics: Citations

This table repeats the analysis of Table 7, 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.

	Citations to U.S. Startup Patents			
	(1)	(2)	(3)	(4)
$\mathbb{1}${Event Year = -5}× Treated	-0.164***	-0.164***	-0.164***	-0.164***
	(0.055)	(0.055)	(0.054)	(0.054)
$\mathbb{1}${Event Year = -4}× Treated	-0.143***	-0.143***	-0.163***	-0.163***
	(0.053)	(0.053)	(.051)	(0.051)
$\mathbb{1}${Event Year = -3}× Treated	-0.109*	-0.109*	-0.106**	-0.106**
	(0.056)	(0.056)	(0.0595)	(0.054)
$\mathbb{1}${Event Year = -2}× Treated	-0.078	-0.078	-0.104*	-0.104*
	(0.054)	(0.054)	(0.053)	(0.053)
$\mathbb{1}${Event Year = 0}× Treated	0.097*	0.097*	0.070	0.070
	(0.052)	(0.052)	(0.050)	(0.050)
$\mathbb{1}${Event Year = 1}× Treated	0.283***	0.283***	0.257***	0.257***
	(0.067)	(0.064)	(0.064)	(0.064)
$\mathbb{1}${Event Year = 2}× Treated	0.246***	0.246***	0.220***	0.220***
	(0.067)	(0.067)	(0.064)	(0.064)
$\mathbb{1}${Event Year = 3}× Treated	0.336***	0.336***	0.283***	0.283***
	(0.074)	(0.074)	(0.070)	(0.070)
$\mathbb{1}${Event Year = 4}× Treated	0.362***	0.362***	0.343***	0.343***
	(0.074)	(0.074)	(0.071)	(0.071)
$\mathbb{1}${Event Year = 5}× Treated	0.404***	0.404***	0.364***	0.364***
	(0.080)	(0.080)	(0.076)	(0.076)
Country×Class FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Treatment Definition	Majority of startup patents in class c		Mode of startup patents in class c	
R-squared	0.339	0.339	0.326	0.326
Observations	14,310	13,752	15,764	15,764

Table 9
Heterogeneity by Basicness of Patent Classes

This table examines whether the baseline results of Table 5 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 as defined in Table 5. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Patent Applications

	Patent Applications			
	High Basicness	Low Basicness	High Basicness	Low Basicness
	(1)	(2)	(3)	(4)
	(1)	(2)	(3)	(4)
Post	7.2788*	9.6680***	9.4445**	9.3583***
	(4.1758)	(2.4002)	(3.6441)	(2.2368)
Post×Treated	12.9449***	-4.7501*	8.6204**	-3.4738
	(4.6789)	(2.7811)	(3.6312)	(2.5769)
Country×Class FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Treatment Definition	Majority of startup patents in class c		Mode of startup patents in class c	
P-value of Difference	0.006		0.014	
R-squared	0.8703	0.9120	0.8369	0.8844
Observations	7,041	7,032	7,788	7,798

Panel B: Citations to U.S. Startup Patents

	Citations to U.S. Startup Patents			
	High Basicness	Low Basicness	High Basicness	Low Basicness
	(5)	(6)	(7)	(8)
Post	-0.0357	-0.1308**	0.0321	-0.1020**
	(0.0800)	(0.0528)	(0.0766)	(0.0495)
Post×Treated	0.3309***	0.3185***	0.2757***	0.3003***
	(0.0898)	(0.0908)	(0.0852)	(0.0897)
Country×Class FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Treatment Definition	Majority of startup patents in class c		Mode of startup patents in class c	
P-value of Difference	0.877		0.800	
R-squared	0.7615	0.8275	0.7581	0.8181
Observations	7,008	7,060	7,788	7,798

Table 10
Heterogeneity by Secrecy of Patent Class

This table examines whether the baseline results of Table 5 vary across patent classes that differ in their government secrecy. *High Secrecy* is an indicator equal to one if class c has any patent applications with government secrecy orders submitted in year t. *Low Secrecy* is an indicator equal to one if class c has no patent applications with government secrecy orders submitted in year t. The sample and all other variables are as defined in Table 4. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Patent Applications

	Patent Applications			
	High Secrecy	Low Secrecy	High Secrecy	Low Secrecy
	(1)	(2)	(3)	(4)
Post	12.197***	7.959***	14.722***	8.677***
	(3.767)	(2.201)	(4.153)	(1.959)
Post×Treated	23.204**	5.176**	23.685**	3.369
	(9.773)	(2.492)	(11.636)	(2.060)
Country×Class FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Treatment Definition	Majority of startup patents in class c		Mode of startup patents in class c	
P-value of Difference	0.021		0.106	
R-squared	0.955	0.874	0.904	0.842
Observations	874	13,157	1,052	14,497

Panel B: Citations to U.S. Startup Patents

	Citations to U.S. Startup Patents			
	High Secrecy	Low Secrecy	High Secrecy	Low Secrecy
	(5)	(6)	(7)	(8)
Post	0.590***	-0.149***	0.522***	-0.100**
	(0.180)	(0.046)	(0.152)	(0.044)
Post×Treated	0.388	0.342***	0.455*	0.314***
	(0.277)	(0.048)	(0.233)	(0.046)
Country×Class FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Treatment Definition	Majority of startup patents in class c		Mode of startup patents in class c	
P-value of Difference	0.789		0.326	
R-squared	0.852	0.793	0.854	0.785
Observations	874	13,157	1,052	14,497

Table 11
Determinants of Cross-Border Investment

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. 1^{st} and 2^{nd} lags look at this variable one year and two years after the investment event correspondingly. All regressions include country and year FEs. 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)
R-squared	0.040	0.040	0.002	0.005
Observations	71,646	56,108	71,646	56,108

Table 12
Foreign Investment and U.S. Startup Activity

Observations are at the patent class by year level. *New startups* are U.S. startups with their first patent submitted in year t in class c. *All active* are all active 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 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 log total foreign CVC investments in class c in year t measured in thousands of U.S. $. Standard errors are clustered on a 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

Appendix

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 Identifier

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

[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.

same company and hence it is removed from the set of names that need to be matched.

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.