Mi Casa Es Tu Casa:
Immigrant Entrepreneurs as Pathways to Foreign Venture Capital Investments

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Research Summary: Venture capital firms predominantly source investments from local networks within tight geographic bounds. Against that tendency, VCs are increasingly investing internationally—but with substantial heterogeneity across firms in extent, location, and success. We propose a mechanism to explain these patterns: the ties VCs form to immigrant entrepreneurs when investing domestically in immigrant-led startups. The knowledge and connections of those immigrants facilitate future VC investments in their homelands. We validate this idea through a study of U.S. VC in India. Firms invest in more Indian startups as their ties to Indian immigrants in the U.S. increase, particularly in the Indian region where immigrants originate and when the VC faces greater domestic competition. Such ties also enhance the odds of successful exit for the VC's Indian investments.

Managerial Summary: Why are venture capital firms increasingly investing in foreign startups, and why do these firms differ in the location and success of such international investments? We demonstrate that ties to immigrant entrepreneurs, established when investing domestically in their startups, provide VCs with knowledge and connections that facilitate future investments in the immigrants' homelands. Using data on U.S. VC firms, we find that the more ties to Indian immigrant entrepreneurs a firm has, the more it subsequently invests in Indian startups. This effect is stronger when the VC firm faces stronger domestic competition (a push effect) and in the specific regions of India where the immigrants originate (a pull effect). Ties to Indian immigrants also help U.S. VCs make more successful investments in India.

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The success of venture capital (VC) firms depends on their ability to obtain information about high-potential startups and access to those startups with some degree of exclusivity. But the quality of a startup is difficult to assess and competition from other investors can undermine access to promising deals (Matusik and Fitza, 2012; Nanda, Samila, and Sorenson, 2020). VC firms have widely adopted a classic solution to these information and competition problems. They rely heavily on social networks composed of ties to other investors, entrepreneurs, and members of the business community to acquire reliable information and gain unique access to potential deals (Hochberg, Ljungqvist, and Lu, 2010; Powell *et al.*, 2005). To promote trust and knowledge transfer, those networks are strongly local (Sorenson and Stuart, 2001, 2008). VC firms thus predominantly invest in geographically proximate startups, and those investments are more likely to be profitable (Bernstein, Giroud, and Townsend, 2016; Chen *et al.*, 2010; Cumming and Dai, 2010).

Against the grain of such localization advantages, VC firms have been increasingly investing in startups located outside their home countries (Ernst and Young, 2015; Hanemann *et al.*, 2019). Cross-border VC violates the proximity rule and adds cultural, legal, and institutional complexities that elevate the already-high uncertainty of investing in a startup. Further adding to the puzzle, some VCs invest abroad more than others, and those that invest differ widely in the location and success of their efforts (Chakma, Sammut, and Agrawal, 2013; Wang and Wang, 2011, 2012). Whatever may be driving VC firm internationalization is thus not industry-specific but rather firm-specific, linked to each VC's idiosyncratic performance calculus. Therefore, it is critical to understand what strategic considerations drive firms to look beyond their local boundaries and why it leads to firm heterogeneity.

We advance one mechanism that helps explain this important issue: differences in VC firms' local ties to immigrant entrepreneurs. Specifically, some of the domestic startups in which a VC invests locally will be founded by immigrants. Those immigrants become part of the VC's network. More ties to immigrant entrepreneurs from a certain country provide the VC with greater access to the home-country knowledge and connections of those individuals, which enable subsequent investments in that country for the VC firm. This is a simple geographical extension of the network mechanism that VCs usually rely upon (Sorenson and Stuart, 2001). But the process does not lead to equal outcomes across firms because some VCs are exposed to immigrant entrepreneurs more than others, and firms are exposed to immigrants of different national backgrounds. Such idiosyncratic exposure over time leads to variance in VC firms' ties to immigrant entrepreneurs from different countries, affecting how much and where firms invest in foreign startups.

Critically, the strategic value of ties to immigrant entrepreneurs may not be the same for all firms or under all conditions. We propose a "pull" and a "push" factor that explain *when* ties to immigrant entrepreneurs will be influential on a VC firm's foreign investment choices.

The pull factor relates to the quality of the immigrant entrepreneurs' knowledge and connections in their homelands. We consider two attributes of individuals' prior experiences that reflect such quality: whether they are first- or later-generation immigrants, and whether they have experience in specific regions of their home countries. First-generation immigrants have direct knowledge and are better connected in the homeland compared to later-generation immigrants. Similarly, immigrants from a particular region of the foreign country provide deeper knowledge and more reliable connections to that region than those from other parts of the same country. Thus, ties to first-generation immigrants should be more influential on the VC firm's decision to invest in the individual's country than ties to later-generation individuals of the same ethnicity. And the firm's choice to invest in a particular region of the foreign country will be most strongly driven by ties to immigrants from that specific region than from other regions.

The push factor reflects the level of competition the firm faces domestically, which creates pressure to consider alternative investment locations. The more investors compete locally for a limited number of startups in their preferred sectors, the harder it is for a VC in that sector to find proprietary deal flow domestically. This pushes the VC firm to consider other frontiers, including those away from its core geographic market. But not all firms are equally aware of foreign opportunities or primed to pursue them. Those with valuable knowledge and connections in specific foreign markets are better equipped to do so, including firms with ties to immigrant entrepreneurs in their local networks. We therefore expect that ties to immigrants will influence a VC firm's investments abroad more strongly during periods when the firm faces heightened domestic competition.

VC firms will pursue foreign opportunities sourced from their ties to immigrants because they expect these to be profitable. But such ties could be channels of inaccurate information or biased connections. We thus consider the critical issue of whether these ties enhance the performance of VC's foreign investments. As already noted, immigrant entrepreneurs can provide knowledge and connections that help VCs identify and access quality deals pre-investment. We also argue that ties to immigrant entrepreneurs can help post-investment by connecting the VC to resources and networks useful for supporting startups' growth and for negotiating a profitable liquidation of the investment. If these mechanisms are in play, we should observe that

the likelihood of a successful exit for a startup that received foreign venture capital should be higher the greater the domestic exposure of the VC firm to immigrant entrepreneurs from the startup's country.

We find support for these ideas using data on the investments of U.S.-headquartered VC firms in India during 2006-2019. The more ties to Indian immigrant founders that a VC firm establishes via its U.S.-based investments, the more the VC subsequently invests in Indian startups. Consistent with the "pull" factor, the effect holds only for ties to first-generation Indians but not for ties to later-generation Indians, and the effect is significantly stronger for investments in the specific regions of India where the immigrants originate (Southern vs. Western India). Consistent with the "push" factor, Indian immigrants have a meaningfully stronger impact on VC firms' investments in India when competition for deals in the VC firms' primary domestic segment is higher. Finally, the likelihood of a successful exit (acquisition or IPO) for Indian startups is higher the more ties the VC firm has to Indian immigrant entrepreneurs in the U.S.

These results do not appear to be driven by a spurious correlation between a VC's exposure to Indian immigrant entrepreneurs and its subsequent investments in India. We account for several 'selection' mechanisms, of which we only mention a few here. First, certain sectors with a high representation of Indian talent across the U.S. and India may become concurrently attractive, leading to correlated investments across the two countries. But our results hold if we limit the sample to investments in Indian startups in sectors different from those of the U.S.-based startups led by Indian immigrants. Second, first-generation immigrants could systematically differ in quality from later-generation immigrants. Yet we do not find meaningful differences in indicators of quality across the startups in which the two participate. Third, the performance results are not driven by VC firms with ties to immigrants in the U.S. selecting late-stage Indian investments that provide a quick liquidity event. Such ties facilitate successful exit even after we limit the sample to early-stage investments in Indian startups. Fourth, the founders of the Indian startups could be using their contacts in the U.S. to procure funding from U.S. VCs with a propensity to invest in Indian founders, instead of the U.S.-based immigrants providing knowledge and connections to the VC. But our results remain unchanged when we eliminate Indian startups whose founders have prior connections to the U.S. Fifth, investments in domestic startups led by immigrants and in foreign startups could simply proxy for a VC's growing international orientation, not knowledge or connections pertaining to a specific country. Yet several placebo tests reveal that ties to Indian immigrants affect VC's investments in India only, not in other countries, and

that ties to entrepreneurs of other national origins have no effect on firms' investments in India or in the success of such investments.

We make several important contributions, most notably by advancing a mechanism that explains when VC firms would eschew the well-understood benefits of local investing while also providing a strategic explanation for why firms vary in the extent, location, and success of their foreign investments. We build on the established network-driven process by which VC firms source their investments (e.g. Sorenson and Stuart, 2001), but add to it by explaining how seeding VC's networks with immigrant entrepreneurs can precipitate foreign investments—contingent on characteristics of the individual immigrants and the VC firms involved. We illuminate novel conditions under which ties to immigrants are strategically valuable for firms: differences in the quality and geography of immigrants' prior experiences draw the firm to distinct opportunities abroad (pull), while changes in domestic competition affect the timing of when firms find those opportunities strategically valuable (push). Crucially, we highlight the value of VC's ties to immigrants by showing their positive association with the performance of these firms' foreign investments.

BACKGROUND

The profitability of venture capital (VC) firms depends on their ability to identify promising startups (a.k.a. "dealflow"), access those startups with a reasonable degree of exclusivity, and help them achieve a successful liquidity event or "exit" (usually via IPO or acquisition). The inherent uncertainty and risk surrounding startups makes these activities challenging. The industry exhibits the classic problems of information asymmetry (Arrow, 1974). In terms of identifying quality startups, not only do VCs have to screen firms and founders for their current quality, they also must make bets on how the people and organization will perform in a future of unknowable states. When it comes to accessing startups, VCs often face the difficulty of competing with rival VCs for the same startups, which can make an investment unattractive even (or especially) when the startup is promising because valuations get pushed up (Nanda *et al.*, 2020). Finally, potential buyers experience meaningful uncertainty when the VC firm is trying to sell its equity stake to new owners (e.g. acquirers or IPO investors).

If the VC industry displays all the problems of information asymmetry, it also exhibits one of its classic solutions: reliance on informal, social mechanisms that help reduce uncertainty (Arrow, 1974; Granovetter, 1985; Rangan, 2000). Prior work has systematically documented at least two such mechanisms: geographic proximity and social networks. The two are intimately related. Many studies have demonstrated

the fundamental role networks play in shaping the types of deals VC investors can access (e.g. Sorenson and Stuart, 2001, 2008), as well as their ability to foster the success of the companies in which they invest (e.g. Hochberg, Ljungqvist, and Lu, 2007; Ter Wal *et al.*, 2016). The empirical literature has primarily focused on syndication (co-investment) networks among VC firms, while recognizing that other connections (to entrepreneurs, bankers, etc.) also matter. The networks of VCs are geographically localized (Cai and Szeidl, 2018; Sorenson and Stuart, 2001). The social cohesion arising from dense local ties facilitates rich information flows and monitoring (Coleman, 1988; Reagans and McEvily, 2003). This helps VCs alleviate the uncertainty around their investments and closely support startups as they grow post investment (Ter Wal *et al.*, 2016). The information circulating within these networks is thus overwhelmingly local in content. Hence, multiple studies have shown that VC's are much more likely to make investments in local startups (Chen *et al.*, 2010; Cumming and Dai, 2010) and that doing so is associated with superior financial performance (Bernstein *et al.*, 2016).

These social mechanisms provide a good explanation for the pattern of localization seen in the VC industry. But they do not seem as well suited to explain two related phenomena mentioned in the introduction: the meaningful growth in cross-border VC investment, and the significant heterogeneity across VC firms in the extent, location, and performance of their cross-border investments. Something must be loosening the tendency towards localization; but doing so in a way that affects firms differentially. The mechanism cannot be a uniform external stimulus—a common factor at the level of the industry, home country, or foreign country—that leads to similar international investment behavior among VCs. We propose one mechanism that can account for the distinct foreign investment choices and performance among VC firms: the heterogeneous ties of VC firms to immigrant entrepreneurs.

Immigration and Cross-Border Investment

Before proceeding to our arguments and hypotheses, we briefly review a few relevant precedents linking immigration to cross-border investment.

Foreign direct investment (FDI) can help firms find new markets, lower production costs, or develop novel capabilities. Yet the liabilities associated with operating in foreign markets are well documented (Zaheer, 1995). Foreign firms find it hard to assess the opportunities and risks of potential new markets ex-ante, and struggle to adapt to cultural, institutional, and other differences ex-post (Ghemawat, 2007). Hence, much of the research and managerial effort in global strategy revolves around finding factors that ameliorate

the risk and uncertainty of FDI. Immigration has increasingly been shown to be one such factor. The core idea is that migrants have spanned many of the differences that make investment risky across the sending and receiving location, and thus form a vector of knowledge and relationships that lubricate exchange across borders. The first set of studies getting at this idea focused on macro-level trade and investment, showing that these are linked to bilateral migration flows across countries (e.g. Bandelj, 2002; Foad, 2009; Gould, 1994; Leblang, 2010).

These results piqued the interests of business scholars because firms are the primary drivers of cross-border investment. Studies have shown that firms tend to favor foreign locations with larger populations of immigrants from their home countries, and that these investments tend to perform better (Burchardi, Chaney, and Hassan, 2019; Cohen, Gurun, and Malloy, 2017; Hernandez, 2014; Li, Hernandez, and Gwon, 2019). Some work has proposed mechanisms explaining these relationships, including factors such as knowledge transfer (Choudhury and Kim, 2019; Hernandez, 2014), cost savings (Kulchina, 2016), and trust (Li *et al.*, 2019). A strand of this research has examined the role of returnees (i.e. individuals who move back home after living abroad) as drivers of cross-border flows of knowledge and capital (e.g. Li *et al.*, 2012; Liu *et al.*, 2010; Wang, 2015). For instance, Nanda and Khanna (2010) showed that returnee entrepreneurs in India are more likely to rely on foreign sources for business leads and financing.

Cross-Border Venture Capital and Immigration. Most research examining the antecedents of cross-border VC has largely focused on country-level factors, with an emphasis on legal, institutional, and cultural variables (e.g. Aizenman and Kendall, 2012; Bradley *et al.*, 2019; Devigne *et al.*, 2018; Guler and Guillén, 2010). Most directly relevant to our study, population-level immigration has previously been linked to cross-border VC investment at the macro level. Using country-level data, Madhavan and Iriyama (2009) demonstrated that aggregate VC outflows from the United States to other countries are related to the volume of professional and technical immigration from those countries into the U.S. Iriyama, Madhavan, and Li (2010) further showed that the aggregate amount of VC exchange between foreign countries and U.S. states is related to the patterns of immigration across the two.

We advance this literature by addressing three significant gaps. First, while previous research broadly argues that human networks provide useful information that facilitates cross-border VC, it examines this mechanism at the population level and thus does not explain differences in the behavior of VC firms exposed to the same population of immigrants. Consider two VCs from Silicon Valley, both equally exposed to the

same population of Indian immigrants. Previous work offers little insight into these firms' differential investments in India, which can be substantial. Second, prior research does not consider the strategic imperatives of the VC firms themselves, which will determine whether and when these firms are likely to leverage their connections to immigrants, or indeed whether individual immigrants may differ in the way they influence the investments of these VC firms. Finally, prior research has not considered the influence of immigrants on the performance of VCs foreign investments—immigrants may be influencing VCs to invest in their homelands, but such investments may not be optimal for the VCs.

We address each of these issues by lowering the level of analysis and adopting the perspective of a VC firm strategically seeking out a proprietary deal flow. We focus on individual immigrants and define a tie as formed when VCs invest in startups led by individual immigrants, instead of inferring potential ties based on exposure to an immigrant population. This allows us to explain why two firms in the same location may end up with ties to different numbers of immigrants of the same nationality, which leads to heterogeneity in the VC's foreign investments. We explore variance in the conditions under which VC firms value the knowledge and connections provided by their ties to immigrant entrepreneurs (the "push" and "pull" factors discussed in the introduction). And we directly assess how ties to immigrants affect the performance of VC firms' investments in the immigrants' homeland. All these advances are new to the literature, offering a valuable strategic perspective relative to prior work focused on more macro-level phenomena.

HYPOTHESES

We mentioned three key activities that directly affect the success of VC investments: identifying promising startups, gaining reasonably exclusive access to those startups, and facilitating a profitable exit. VC firms will invest in foreign startups if they believe they can perform those activities well abroad. To formalize our hypotheses, we first explain *how* the ties of VC firms to immigrant entrepreneurs can facilitate these activities. We then explore factors that explain *when* ties to immigrants are most valuable for these firms: the "pull" from the quality of immigrants' knowledge and connections and the "push" of domestic competition. Finally, we consider the ultimate *performance* of the VC's foreign investments.

Ties to Immigrant Entrepreneurs and Foreign Investments

Venture capitalists work closely with the individuals in whom they invest, resulting in relationships of trust and knowledge sharing. Studies show that these relationships influence future investments. For example: "venture capitalists repeatedly finance investments that they learn about through referrals from

close contacts, including entrepreneurs that the capitalist previously financed…" (Sorenson and Stuart, 2001: 1553). Our own interviews with multiple VC firm partners confirmed that the entrepreneurs they work with are frequently the source of information and connections that lead to new investments.

Our argument linking firm's ties to immigrant entrepreneurs and their foreign investments represents a simple extension of the network mechanism that prior work has already documented. As VCs go about seeking profitable investments through their usual local ties, they invest domestically to varying degrees in startups with immigrant individuals among the founding or management team. These immigrants enter the network of trusted entrepreneurs in which the VC previously invested, potentially providing information and connections that facilitate new investments for the VC. Compared to natives, immigrant entrepreneurs are unique nodes in a VC's network because they have contacts and knowledge across the sending and receiving countries. Research on transnationalism documents that immigrants do not simply sever their relationships, activities, and interests in their homelands upon arrival in the receiving country (Waldinger, 2015). While immigrants have strong incentives to assimilate, they also maintain webs of social, economic, and political networks spanning the two geographies (Levitt, 2001). Thus, they play at least two critical roles that facilitate cross-border business activity. First, immigrants help transfer the latest ideas, information, and other resources across locations (Portes, 2001; Wang, 2015). Second, having overcome cultural, institutional, and geographic frictions, immigrants serve as translation interfaces between natives across the two locations who may benefit from doing business but might not find, understand, or trust one another in the absence of an intermediary (Li *et al.*, 2019; Choudhury and Kim, 2019).

Because of the transnational nature of immigrants' experiences, at least some of what flows to VCs through their ties to immigrant entrepreneurs will likely pertain to the entrepreneurs' homelands. Further, the knowledge and connections provided by such ties is credible and trustworthy. The work we cited earlier demonstrates that immigrant networks are powerful enough to spur firms to engage in FDI across borders (Foley and Kerr, 2013; Hernandez, 2014; Iriyama *et al.*, 2010). Closer to our context, Saxenian (2007) documents how highly skilled immigrants facilitated investments, managerial appointments, and technology transfer between technology firms in Silicon Valley and their business partners in Asia. One example is that of Thuan Pham, a Vietnamese refugee who played a critical role in shepherding investments in Vietnamese startups while serving as the CTO of Uber (Julka, 2016). Our own interviews with VCs and entrepreneurs confirmed the importance of ties to immigrant founders for VC firms. For example, a partner from a Silicon

Valley firm described how this plays out, saying "*I was in India last week, and met with 7 or 8 companies. Half of them were introductions from our local (US-based) founders and people they are connected to*."[1]

Over time, the process of investing in startups led by immigrants leads some VC firms to accumulate more information and connections to opportunities for investments in foreign countries than other VCs who happened to not be as exposed to immigrant entrepreneurs. The more exposed firms can better screen potential foreign opportunities for quality—one of the critical inputs into VC success. Further, inasmuch as VC firms vary in their links to immigrants from different parts of the world, the geography of the international opportunities to which they are exposed will also differ. This process preserves the social network mechanism described in prior research—but extends its geographic reach. We do not imply that proximity ceases to be an important or even dominant pattern in the industry. Rather, heterogeneity in exposure to immigrants provides an explanation for why some firms make an exception to the proximity rule and to which foreign markets they are drawn. Thus,

> *Hypothesis 1: The more ties a VC firm establishes with immigrant entrepreneurs from a certain country through its domestic investments, the more the VC firm will subsequently invest in startups located in the immigrants' home country.*

We now account for factors that create variance in the conditions under which different VC firms will find ties to immigrant entrepreneurs to be strategically valuable.

Pull Factor: Quality of Immigrants' Knowledge and Connections

The driving mechanism behind the previous hypothesis is that immigrant founders have good information and reliable connections in their homelands. An alternative explanation may be that exposure to individuals of a certain nationality leads to subsequent investments simply because it draws the firm's attention to the country of those individuals, but without providing any tangible knowledge or connections. If our foregoing argument is correct, however, and immigrant founders influence VC firms' investments based on factors that augur improved performance, then we should observe that the relationship embodied in

[1] We are portraying the process of establishing ties to immigrant entrepreneurs as idiosyncratic and unrelated to subsequent choices to invest abroad because that is what we discovered during our interviews. VCs cannot anticipate the future outcomes of relationships formed with specific entrepreneurs, whether those individuals are natives or immigrants. The opportunities and resources from relationships with past founders arise ex-post. Some readers may be concerned that certain 'selection' factors simultaneously drive VC firms' ties to immigrant entrepreneurs and subsequent choices by the VC to invest in the homelands of those immigrants, even if VCs are not instrumentally seeking out immigrant founders with the intention of investing in those founders' homelands. We take extensive steps to empirically deal with potential 'selection' concerns, as reported later. In our theorizing, however, we present the process consistent with our interviews and with prior work describing how VC networks operate.

hypothesis 1 is stronger the higher the quality of the home-country knowledge and networks of the immigrants to which the VC is connected. We consider two sources of variance on that dimension.

First, as VC firms invest in domestic startups with immigrant founders, they could form ties to individuals who were born in and spent significant time in their homelands before emigrating as adults (actual immigrants) or to ethnic individuals who are descendants of actual immigrants from the same homeland (children, grandchildren). The first group is clearly more likely to have direct knowledge about relevant business issues and to know people in the business environment of the homeland. For instance, an individual who emigrated from India as an adult will know people from their working or university days who are currently in positions or industries that may be relevant to a VC firm considering investing in India. Later-generation immigrants of the same ethnicity, in contrast, may be aware of and interested in the business environment of their homeland, but are less likely to provide tangible resources that help the VC make better decisions about foreign investment prospects. If firms view ties to immigrants as a mechanism to identify profitable investments abroad, we should observe that:

> *Hypothesis 2a: A VC firm's ties to immigrant entrepreneurs (first-generation) will have a stronger impact on the number of subsequent foreign investments made by the VC firm in the immigrants' home country than ties to entrepreneurs of the same ethnicity who are not first-generation immigrants (i.e. second- or later-generation).*

Second, even within the group of first-generation immigrants from the same country, there are differences in the specific regions of the home country in which they have had meaningful first-hand experiences. An individual will have the best information and access to relevant contacts in places where they have spent considerable time and had formative experiences. Returning to the example of the Indian immigrant, that person will have more knowledge and connections in Bangalore than Mumbai if she grew up, studied, or worked in Bangalore instead of Mumbai. And she will be more useful as a source of information and resources for a foreign VC considering an investment in Bangalore than Mumbai. Hence, VC firms will receive the highest quality information and connections pertaining to the sub-region from which a first-generation immigrant originates. Therefore,

> *Hypothesis 2b: Ties to immigrant entrepreneurs will have a stronger impact on the number of foreign investments made by the VC firm in the region of the country from which the immigrants originate than in other regions of the same country.*

Push Factor: Domestic Competition Faced by the VC Firm

The exclusivity of a VC's deal flow is critical to its performance. VC firms often compete fiercely for access to the most promising startups. When that happens, it becomes hard to access desirable startups at an attractive valuation, and VCs are forced to sacrifice profits or to seek for other investments. When a VC firm faces little domestic competition for startups in its desired investment segment, the imperative to consider geographic diversification is weak because the firm can source unique deals in that market. Why take on the added risks of cross-border investments when the domestic market, in which the firm is well-known and well-connected, has attractive prospects?

But when saturation in the domestic market increases, heightening competition for a limited set of opportunities, the VC firm experiences a push to consider new horizons. Indeed, this has been a concern in many VC markets, such as Silicon Valley, due to an increase in investment capital flowing to the same deals (Lazarow, 2020). When faced with such a push factor, VC firms should be more receptive to the opportunity of new and unique deal flow in foreign markets. Further, heightened domestic competition can also influence the firm's limited partners (i.e. capital provides) to become more open to new markets. LPs typically set parameters for how general partners (VCs) can invest their capital, such as rules regarding acceptable industries or geographies (Hochberg and Rauh, 2013; Sahlman, 1990). We confirmed that this can be a limitation on the geographic scope of VC's investments in interviews with industry participants. When competition constrains access to profitable deals in the primary market, limited partners are likely to become more open to allowing the VC to invest in a broader set of markets, including foreign countries.

Yet not every VC firm facing increased domestic saturation will consider foreign opportunities or be able to pursue them. How firms expand their investment horizons when under pressure depends strongly on the opportunities available through their existing networks. Relationships with individuals connected to specific foreign markets are an important vehicle by which VCs learn about and evaluate opportunities in those markets. We thus posit that increased competition in the VC firms' primary domestic market will make the immigrant contacts in the VC firm's network more salient. The same firm may thus respond differently over time to the foreign opportunities available from its ties to immigrant entrepreneurs, as competition leads to fluctuating strategic needs. Thus,

> *Hypothesis 3: The higher the competition for deals in a VC firms' primary domestic market, the stronger the effect of ties to immigrant entrepreneurs on the number of foreign investments subsequently made by the VC firm in the immigrants' home country.*

Ties to Immigrant Entrepreneurs and Foreign Investment Performance

Ties to immigrant entrepreneurs should also enhance the success of VC's investments abroad. We focus here on achieving a successful exit—the third crucial activity influencing VC performance (Hellmann and Puri, 2002; Lerner, 1995). We already argued how ties to immigrants can help VCs obtain a high-quality and unique dealflow, which helps VCs select better deals in the immigrants' homelands. These ties can also be valuable when it comes to post-investment activities by helping procure valuable resources for the startup. When the VC is actively working with the startup, those resources include personnel, technology, suppliers, distributors, etc. And when the VC is seeking to liquidate the investment, those resources include connections to prospective investors such as potential acquirers or actors involved in the IPO process (Kaplan and Strömberg, 2004; Sapienza, 1992). Being connected to immigrants with first-hand experience and connections in the foreign market can be helpful when those resources are located abroad (e.g. a referral to an investment banker friend or a relative with needed job skills).

If our proposed mechanisms are at play, we should ultimately observe that ties to immigrants are associated with more successful investments in the immigrants' home country. Yet this is not a given. Like with all network ties, those to immigrants may be channels of biased knowledge or unreliable connections. Social mechanisms such as homophily, attention-drawing, or path dependence could lead VCs' make suboptimal investments based on outdated information or opportunistic contacts in the homeland (Lin, 2001; Uzzi, 1998; Gargiulo & Benassi, 2000). These dysfunctional mechanisms could still lead VC firms to invest in the immigrants' homeland, but they would not lead to good performance. Thus, exploring the performance effects of ties to immigrants is a critical empirical question. Therefore, we propose that:

> *Hypothesis 4: The more ties a VC firm establishes with immigrant entrepreneurs through its domestic investments, the more successful will be the VC firm's subsequent investments in the immigrants' home country.*

DATA

We empirically examine these issues using a sample of investments by U.S. VC firms in India. The setting has several features that fit our research objectives. First, India is one of the three largest foreign destinations of U.S. VC, offering a sufficiently large set of observed investments to analyze. Second, Indians engage in substantial entrepreneurial activity in the U.S., providing a sufficiently large set of VC-funded startups in which Indian immigrants are represented. Third, large-scale immigration from India to the U.S. is recent enough that Indians remain ethnically distinct (especially compared to other groups such as Germans

and Italians), but established enough to clearly distinguish first- vs. later-generation immigrants. Indians began arriving in meaningful numbers after the Immigration and Nationality Act of 1965, with the majority entering after the year 2000 (Zong and Batalova, 2017). Finally, Indian names have unique features that help us disambiguate Indians from people of other ethnicities and test important conceptual mechanisms, as we explain later. Other immigrant groups in the U.S. (e.g. Chinese or Israelis) share some of these characteristics but none of them provide all these empirical advantages.

We collected information from *VentureXpert* on the 100 largest VC investors from the U.S. While our findings may not generalize to small VC firms, three critical considerations informed our decision to focus on large VCs. First, the top 100 firms capture the lion's share of the U.S. VC ecosystem, or 45 percent of all deals listed in *VenturXpert*. Second, they represent an even larger share of foreign investments, or nearly 60 percent in *VentureXpert*. That share would be significantly larger in amount invested, but we could not reliably quantify that because deal size is often not disclosed for small deals or small VCs. Third, obtaining biographical information on the founders of the startups in which VCs invest requires a non-trivial amount of manual work. For the deals made by the top 100 firms, for example, we had to identify and obtain biographical information on individuals involved in nearly 8,000 startups.

We ended up dropping two large private equity firms (the Carlyle Group and Warburg Pincus) that make VC investments but are strategically and operationally distinct from typical VCs. For each of the remaining 98 firms, we identified all investments in U.S.-based startups involving Indian immigrant entrepreneurs from 2005-2014, and their subsequent investments in startups located in India during 2006-2019. We also collected data on the educational and ethnic backgrounds of the entrepreneurs and of the managers of the VC firms from sources described later.

Variables

Dependent variables. The first outcome of interest is the *number of Indian startups* in which each U.S.-based VC firms invests. We count those investments during the five years following the focal year (e.g. 2013-2017 if the focal year is 2012). The results are robust to other time windows (see appendix). We have data on investments in India for the period 2006-2019, so the last focal year is 2014. We only consider the first investment made by the VC in each Indian startup because the mechanism by which ties to immigrants help VCs applies mainly to the initial opportunity. Subsequent investments in the same startup bring up other

factors that would confound the mechanism of interest. To test H1b, we break down the investment counts by subregion within India (Bangalore, Mumbai, and the rest).

The second outcome of interest is the performance of the VC firms' investments in India. Consistent with prior research, we use the indicator variable *exit* as a proxy for performance (e.g. Alvarez-Garrido and Guler, 2018; Park and Steensma, 2012). We code exit as 1 if the Indian startup experiences any of three possible liquidity events: it is acquired by another firm, it is listed on the stock market (IPO), or the focal VC sells its stake in a secondary sale (typically to a private equity firm) (Gompers *et al.*, 2010). We obtain data on these outcomes from *Venture Intelligence*, an India-focused VC database (see Claes and Vissa, 2020).

We note that the unit of observation for the two dependent variables differs. *Number of Indian startups* is measured for each VC firm-year, whereas the liquidity events counted in *exit* are measured for each investment dyad (i.e. VC firm-Indian startup). This requires different estimation approaches for each outcome, as we explain below.

Independent variables. We count the number of *ties to Indian immigrants* formed by U.S. VC firms each year between 2005 and 2014. We consider a tie formed in the year the VC invests in a startup where the immigrant is a founder or CEO, and we count each individual immigrant as a separate tie. To create this variable, we collected information on the ethnic and educational background of the founders and CEOs of all 7,875 startups that received investment from the 98 VCs in our sample. We built a web-scraping algorithm that looked up the last name of each individual on *www.forebears.io* and determined the country in which it was most common (e.g. Kerr, 2008 uses a similar approach). We flagged all individuals whose last name was most common in India. To be comprehensive, we also included individuals with last names most common in Bangladesh, Pakistan, or Sri Lanka. This approach works for India because of the linguistically distinct nature of Indian names. We manually verified that every name flagged by the algorithm was in fact Indian. We then went a step further and manually gathered information on each individual's professional background, using *LinkedIn* primarily (complemented by *Bloomberg*, *archive.org*, and other sources).

To distinguish between first-generation and later-generation immigrants, we rely on the country of their undergraduate institution. We categorize someone as an Indian immigrant if they have an Indian last name plus an undergraduate degree from an Indian university. This is the basis for our main independent variable, *ties to Indian immigrants*: the number of first-generation immigrants to which the focal VC firm became connected through its domestic investments in the focal year. In contrast, if individuals have an

Indian last name but an undergraduate degree from a U.S. university, we consider them later-generation immigrants of Indian ethnicity. These individuals are the basis for the variable *ties to later-generation Indians*, measured by counting the VC firm's ties to later-generation Indians through its domestic investments in the focal year. We use *ties to later-generation Indians* to test H2a and include it as a control in all models.

Our rationale for the distinction is as follows. Though the number of Indians moving to the U.S. for undergraduate degrees has been increasing, by 2013 undergraduates comprised only around 10% of Indians on student visas in the U.S. (IIE Open Doors, 2013). Recall that we observe Indian immigrants only up to 2014, and they show up as entrepreneurs in our sample years after their university studies. The vast majority of Indian students in the U.S. still move to pursue graduate degrees (Masters or PhDs). Another major path by which Indians immigrate to the U.S. is to work, typically on the basis of technical skill (i.e. H1-B visas). To qualify for work visas, these individuals must have at least an undergraduate degree. Consequently, during our sample period an Indian entrepreneur with an undergraduate degree from the U.S. is overwhelmingly likely to be a second- or later-generation immigrant. Our classification is conservative because we are not counting first-generation Indians that entered the U.S. as children or to get an undergraduate degree. This also ensures that those counted as first-generation immigrants have had meaningful experiences in India as adults, making it plausible that they have relevant knowledge and connections back home.

Hypothesis 2b requires distinguishing immigrants by their previous experience in distinct regions of India. U.S. VC investments in India are primarily located in Mumbai and Bangalore, each accounting for roughly 30% in our sample. Bangalore is the commercial hub of Southern India, consisting of five states (Karnataka, Kerala, Tamil Nadu, Andhra Pradesh, and Telengana). Mumbai is the hub of Western India, consisting of three states (Maharashtra, Goa, and Gujarat). We relied on two indicators to surmise whether the immigrant entrepreneurs in our sample had meaningful connections to Bangalore, Mumbai, or neither. The first is whether their last names are characteristic of the region, because names from the two regions are distinct and relatively easy to classify (e.g. Menon is from the South and Tendulkar is from the West). The regions embody centuries-old linguistic and cultural characteristics that markedly distinguish them from each other and the rest of India (Steever, 2015). Because internal migration in India is extremely low compared to other countries (Bell *et al.*, 2015), family history is a reasonable (albeit imperfect) predictor of where someone has lived. The name coding was done by one of the co-authors, who is Indian, with the help of two Indian RAs. But people may also have meaningful experience in places other than where they grew up. Thus,

the second indicator is if the immigrant received an undergraduate degree from an Indian university in the region, a formative experience even for individuals not having a typical regional name. A relevant study of Swedish graduate entrepreneurs showed that the majority located their ventures where they went to college, especially in metropolitan areas (Larsson *et al.*, 2017).

We thus classify each individual as having connections to a specific region if either their name or their undergraduate institutional is associated with that region (or both) and create three variables of interest: *ties to Indian immigrants (Bangalore), ties to Indian immigrants (Mumbai), ties to Indian immigrants (other regions).* Our findings are robust to using just one of the criteria (i.e. last name or location of undergraduate institution) to classify individuals as being connected to Bangalore or Mumbai.

To examine the competition "push" suggested by hypothesis 3, we measure *total U.S. VC in primary sector* as the amount of VC investment (billions of USD) in the focal year that flows into the industry sector in which the focal VC firm made the greatest number of investments in the previous year. Our results are robust to using two different measures of domestic competition, as we explain in the appendix.

Control variables. We control for a range of factors with the aim of accounting for potential alternative explanations, particularly the selection-related concerns we describe next. All models include VC firm fixed effects (with one exception noted later) to rule out differences across firms, and year fixed effects to account for macroeconomic fluctuations across time. To preserve space, we list the control variables in Table 1, along with the reasons for their inclusion and their measurement.

*** TABLE 1 HERE ***

Accounting for Alternative Explanations

We have hypothesized something akin to a "treatment" effect—connecting with Indian immigrants by investing in their startups leads to a higher incidence and success of investments in India. The most significant alternatives to our proposed mechanism are explanations based on "selection" effects: that VC firms invest in startups founded by Indians in the U.S. for reasons correlated to the incidence, location, and performance of their subsequent investments in Indian startups—with those reasons being unrelated to the knowledge and connections gained *after* forming ties to Indian immigrant entrepreneurs.

In theory, the most direct form of selection would be that VCs invest in U.S.-based startups with the explicit intention of networking with Indian individuals because they plan to invest in India later. This mechanism is unlikely in practice, as we learned through our background research. The VCs we interviewed

expressed that the future information or connections provided by an entrepreneur are not a consideration ex-ante in shaping current investment decisions. Awareness of the potential value of ties to immigrants arises post-investment, as VC's consider subsequent opportunities through the usual network process (Sorenson and Stuart, 2001). Further, VCs focus on the returns of each standalone investment because they have a fiduciary duty to maximize the returns of current funds raised from their limited partners (LPs). An LP would not allow the VC to compromise the returns of current investments for a hypothetical foreign investment of uncertain potential and in which the LP may not even participate.

However, indirect selection mechanisms could lead to a spurious correlation if factors that attract VCs to U.S. startups led by Indians correlate with other drivers of VCs' future (successful) investments in India. We designed our study to mitigate such concerns. We directly account for any such factors that vary across firms through VC fixed effects. We can precisely control for several within-firm, time-varying confounders that are observable (Pearl and Mackenzie, 2018), as detailed in Table 1 (e.g. the VC firm has Indian partners; the firm invests in the IT sector, where Indian talent is disproportionately represented; the VC firm has an office in India; the VC has an India-focused fund; the VC is located in a U.S. city with many Indian immigrants; etc.). Other concerning factors are unobservable, such as correlated trends in the supply of or demand for startups in certain sectors across India and the U.S., the "relatedness" between the U.S.-based and the India-based startups, or the connections of the Indian startups' leaders in the U.S. We take several steps to mitigate these alternative explanations by focusing on sub-sets of investments where these concerns do not exist. We explain these tests at relevant points in the remainder of the paper.

ESTIMATION AND RESULTS

Descriptive Statistics

The VCs in our sample invested in 397 distinct Indian startups during the study period. Table 2 shows that, in any given 5-year window, a firm makes an average of 1.62 investments in India (with a standard deviation of 5). But as figure 1a shows, this is far from evenly distributed: the most common outcome in any 5-year window is to *not* invest in India. Conditional on firms making at least one investment, the most common outcome is 1-2 investments during a 5-year window. These facts are consistent with the tendency invest locally in this industry, and with the high risk of investing in India for U.S. firms.

*** TABLE 2 AND FIGURES 1a, 1b AND 2 HERE ***

We identified 835 entrepreneurs of Indian ethnicity that received VC investment in the U.S., of which 54% were first-generation immigrants. The average firm connects with 1.5 Indian immigrants per year (minimum of 0, maximum of 14). Only 5 of the 98 VCs *never* form a tie to an Indian immigrant entrepreneur, in line with research demonstrating the prominence of Indians in the U.S. startup ecosystem (Wadhwa *et al.*, 2007). Figure 1b shows that firms connect to at least one Indian immigrant via startup investment in roughly 60% of firm-years, with the bulk of firm-years consisting of one to five connections.

Consistent with our expectations, the left panel of figure 2 shows a positive correlation between the number of investments in India and *ties to Indian immigrants*. We do not find a positive association between investments in India and *ties to later-generation Indians* in the right panel. We now turn to our estimation.

Investments in India

We first estimate the effect of *ties to Indian immigrants* on the *number of Indian startups*. The equation of interest is as follows:

$$Indian\ Startups_{i,[t+1,t+5]} = \beta_1 * ties\ to\ Indian\ immigrants_{it} + \beta_2 * X_{it} + \lambda_i + \delta_t + \varepsilon_{it}$$

Indian startups$_{i,[t+1:t+5]}$ is a count of the number of firms in which VC firm *i* invested in India in the five years following the focal year *t*; *ties to Indian immigrants*$_{it}$ is the number of immigrants to which VC firm *i* formed ties through its U.S. investments in year *t*; X_{it} is a vector of control variables; λ_i are VC firm fixed effects; γ_t are year fixed effects; and ε_{it} is the error. The outcome is a count variable, so we estimate the coefficients using negative binomial models. We add VC firm fixed effects by including a dummy for each firm to ensure that we capture only within-firm variation. Given the challenges of interpreting coefficients (especially interactions) in non-linear models, we also employ linear models.

We include only the control variables in model 1 of table 3. In model 2, we introduce *ties to Indians (any generation)*—the sum of ties to Indian immigrants and to later-generation Indians. This variable significantly affects subsequent investments in India (p = 0.005). We break this variable into counts of first- and later-generation Indian entrepreneurs in model 3. *Ties to Indian immigrants* has a strong positive effect on *investments in India* (p = 0.003): each tie increases the number of investments over the next five years by about 9% (roughly 0.15 additional investments relative to the mean). In contrast, the coefficient of *ties to later-generation Indians* is not significant (p = 0.571). The difference between the coefficients is significant (p = 0.036, one-tailed Wald test). These results provide support for H1 and H2a.

*** TABLE 3 HERE ***

We noted earlier how we distinguish between first-generation immigrants from Bangalore, Mumbai, and other regions to test H2b. We also break down the dependent variable to match by separately counting *investments in Bangalore* and *investments in Mumbai*. Table 4 shows the results of these analyses. The outcome in Models 4 and 5 is *investments in Bangalore*, whereas in models 6 and 7 it is *investments in Mumbai*. In model 5, *ties to Indian immigrants (Bangalore)* exhibits a positive and significant impact on investments in Bangalore ($p < 0.001$) and, per a Wald test, has a magnitude significantly larger than that of ties to immigrants from Mumbai ($p < 0.001$) or from other parts of India ($p = 0.002$). In model 7 (Mumbai), *ties to Indian immigrants (Mumbai)* has a positive effect on investments in Mumbai ($p = 0.004$) and its magnitude is substantially larger than ties to immigrants from the other two regions; with Mumbai > Bangalore ($p = 0.038$) and Mumbai > Other ($p < 0.001$) per Wald tests. This lends support to H2b.

*** TABLE 4 HERE ***

To test hypothesis 3, we interact *total U.S. VC in preferred sector* with the VC firm's ties to Indian immigrant entrepreneurs (see table 5). We observe a positive and significant interaction ($p = 0.011$) per the negative binomial estimation in model 9. Because the sign and magnitude of interaction coefficients in non-linear models may be misleading (Ai and Norton, 2003; Leiponen and Helfat, 2010), we take two additional steps. First, because marginal effects change along different points of the non-linear curve, we plot the interaction estimates from model 9 and assess differences in marginal effects across conditions of low vs. high domestic competition (10th vs. 90th percentile) for all values of *ties to Indian immigrants* up to two standard deviations above the mean. Figure 3 contains the full details. On average, each additional tie to an Indian immigrant increases the number of investments in India by the VC firm by about 2% under low-competition conditions vs. 11% under high-competition conditions ($p < 0.001$ for the difference). Second, we run a linear fixed effects regression (model 10) and still find a positive and significant interaction effect ($p = 0.051$). The larger p-value is expected because linear models produce less efficient, but consistent, estimates of non-linear dependent variables (Angrist and Pischke, 2008; Wooldridge, 2010).

*** TABLE 5 AND FIGURE 3 HERE ***

Ties to Indian Immigrant Entrepreneurs and Performance of Investments in India

To test H4, we estimate the odds of successful *exit* using two different approaches. Each approach examines the effect of *ties to Indian immigrants* formed at different times, pre- vs. post-investment, each providing a unique insight into the mechanism by which immigrants affect VC firm performance.

Pre-Investment Ties to Immigrants. First, we follow an approach as similar as possible (though not identical) to the one we used previously to analyze investments in India:

$$Exit_{ij,[t+1,t+5]} = \beta_1 * ties\ to\ Indian\ immigrants_{it} + \beta_2 * X_{it} + \lambda_i + \delta_t + \varepsilon_{it}$$

Here, $Exit_{ij\ [t+1:t+5]}$ is coded as 1 if Indian startup *j* that received investment from VC firm *i* experienced a liquidity event during the five years [*t+1* to *t+5*] following the investment; *ties to Indian immigrants*$_{it}$ is the number of immigrants connected to VC firm *i* through its U.S. investments in year *t* (i.e. only the year *before* investing in the Indian startup *j*); X_{it} is the vector of control variables listed earlier; λ_i are firm fixed effects; and γ_t are year fixed effects. Each row in the data represents a different Indian startup-VC firm pair. To eliminate differences across VC firms that affect startup performance, we include VC firm fixed effects. Thus, these estimates are driven by variance in ties to immigrants across pre-investment years for different investments *by the same VC firm*. (Note that any VC that made only one investment in India drops out of the analysis because it is perfectly identified by the firm fixed effect.)

The results from this analysis are in model 11 of table 6. Ties to Indian immigrants formed before investing in an Indian startup have a positive and significant effect on the propensity of successful exit (p = 0.027). Each additional tie to an Indian immigrant is associated with a 1.4% increase in the probability of exit within the next five years—a 31% increase relative to the average five-year exit probability of 4.5% across all the Indian startups in the sample.

Post-Investment Ties to Immigrants. In addition to their pre-investment influence, the immigrant entrepreneurs in a VC's network could also influence the trajectory of startups post-investment. To investigate this possibility, we estimate the following hazard model:

$$h(Exit_{ijt}) = h_0(Exit_t)\exp\left[\beta_1 * ties\ to\ Indian\ immigrants_{it-1} + \beta_2 * X_{ij,t-1}\right]$$

Here, $Exit_{ijt}$ is coded as 1 if Indian startup *j* that received investment from VC firm *i* experienced a liquidity event in year *t*; *ties to Indian immigrants*$_{i,t-1}$ is the number of immigrants connected to VC firm *i* through its U.S. investments in in the preceding year (*t-1*); and $X_{ij,t-1}$ is the vector of control variables listed earlier. The main differences compared to the previous model are that (a) we measure the changing number of ties to Indian immigrant entrepreneurs over time during the *post-investment* period, and (b) we do not impose a specific time range (e.g. 5 years) to capture *exit*. We run separate models measuring the VC firm's ties to Indian immigrants over time in two ways: (1) as a 'flow' by counting the number of new ties each year *t-1* and (2) as a 'stock' by counting the cumulative number of ties from the year before the VC firm invested in

the focal Indian startup up to year *t-1*. Each row in the data is defined by a VC firm-Indian startup-year (i.e. a dyad-year). The observation period for *exit* begins in the year of investment and continues until a liquidity event happens or until the end of our sample (Allison, 2010). We employ a Cox proportional hazard model, which does not impose assumptions on the shape of the underlying risk (Alvarez-Garrido and Guler, 2018) and accounts for the right-censoring of the data (Cleves *et al.*, 2010).

We summarize the results in models 12 and 13 of table 6. We observe a significant enhancement in the baseline hazard of exit from increases in both the flow ($p < 0.001$) and stock ($p = 0.016$) of ties to Indian immigrant entrepreneurs. We report the effects as odds ratios instead of coefficients, so any number > 1 means that a unit change in the variable increases the odds of exit relative to the baseline rate. Exposure to an additional immigrant entrepreneur roughly doubles the baseline rate in the "flow" model and increases it by about 12% in the stock model. These results are strongly consistent with hypothesis 4.

*** TABLE 6 HERE ***

Additional Tests to Account for Alternative Explanations

We mentioned earlier that uncontrolled-for selection mechanisms could provide alternative explanations that undermine our 'treatment' theory. We now rule out several of these alternatives.

Correlated attractiveness of startups across the U.S. and India. If startups with Indian founders in the U.S. and startups located in India have similar desirable but unmeasured attributes, ties to Indian immigrant entrepreneurs formed via investments in the U.S. would simply proxy for unobserved qualities that draw the VC to invest in both types of startups. One dimension of similarity is the extent to which startups led by Indians systematically operate in the same industry sector across India and the U.S. VCs may seek out investments in certain sectors at different points in time (e.g., "sharing economy" or "software as a service") for reasons including technological breakthroughs, financial viability, media attention, or interest from LPs. If Indian talent both in the U.S. and in India is highly represented in desirable sectors, the results we just reported could be driven by selection into those sectors rather than by the knowledge and connections VCs obtain from ties to Indian immigrants.

To see if this may be driving our results, we assessed how ties to Indian immigrants affect the number and success of investments in Indian startups in *different* industry sectors than the U.S. startups through which the VC firm formed its ties to Indian immigrants. We relied on the Venture Economics Industry Code from *VentureXpert* to code startup industries. Table A1 and A2 of the appendix show the top sectors in which the

VC firms invest in U.S.-based firms led by Indian immigrants, and the most popular sectors for their investments in India, respectively. We compared the industry sectors of the U.S. startups led by Indian immigrants to the sectors of the Indian startups receiving investment form the same VC firm (in the subsequent five years). If there was a match in industry sector, we did not include the Indian startup in the calculation of our dependent variables. Now any association between *ties to Indian immigrants* and outcomes for such unrelated investments cannot be driven by sector-specific selection across countries. Model 14 of table 7 shows that ties to Indian immigrants have a positive impact on the number of investments in India in *unrelated* sectors (p = 0.007). Model 18 of table 8 reveals a significant positive relationship between pre-investment connections to Indian immigrants and the likelihood of exit for startups in *unrelated* sectors (p = 0.036). The specification using a hazard model, not shown, reveals significant results for post-investment ties to Indian immigrants.

*** TABLES 7 AND 8 HERE ***

To ensure that these critical results were not driven by a peculiarity in *VentureXpert*'s industry coding scheme, we tested the robustness of these results to classifying similarity between startups using a text-based analysis of their business descriptions. The procedure is detailed in the appendix, and the results of this alternative approach are shown in Model 15 of Table 7 and Model 19 of Table 8. The results remain highly consistent with our previous estimates, both in magnitude and significance.

Entrepreneurs based in India using their U.S. networks. Another plausible alternative is that the entrepreneurs based in India use their ties to the U.S. to raise capital from U.S.-based VCs (Nanda and Khanna, 2010), being more likely to approach and find success with firms that invest more in U.S. startups with Indian founders. Such a mechanism would have nothing to do with the knowledge or networks of the U.S.-based immigrants in the VC's network, but instead capture the VC's predilection to invest in Indians regardless of where they live. To rule this out, we collected information on the backgrounds of the senior managers of the Indian startups that received investments from our sample U.S. VC firms. We then identified the subset of these individuals who either lived or worked in the U.S. before returning to India and founding a startup. Of the 735 individuals we identified, 151 are returnees (about 21%).

We drop the startups associated with the returnees and recalculate the first outcome variable as investments in Indian startups *without any ties to the U.S.* Model 16 of table 7 reveals that ties to Indian immigrants still have a positive relationship with that outcome (p = 0.016). For similar reasons, startups with

returnee founders may eventually be more successful. We therefore re-estimate the exit models after dropping returnee-led startups. Model 20 of table 8 shows that ties to Indian immigrants continue to positively affect the odds of exit for this non-returnee subsample ($p = 0.022$). Our findings are thus unlikely to be driven by founders in India activating their networks in the U.S.

Late-stage investments. Ties to Indian immigrants could merely function as a means for VCs from the U.S. to identify foreign investments involving low risk and a quick liquidation opportunity—a form of international arbitrage that indicates a different mechanism than the one we advance as explaining our findings. This possibility would apply to reasonably mature startups receiving late-stage capital. To rule this out, we re-estimate the *exit* models based only on a sample of early-stage investments made by U.S. VCs in India: those in the very first round of funding the startup receives from any source (local or foreign). Model 21 of table 8 reveals a positive impact of ties to Indian immigrants on the exit of such early-stage investments ($p = 0.003$). Model 17 of table 7 shows that ties to Indian immigrant entrepreneurs also positively affect the number of early-stage investments in Indian startups ($p < 0.001$). Thus, the "quick exit" mechanism does not seem to be driving the main results.

An uptick in the firm's international orientation. A rise in the number of investments in domestic startups led by immigrants, followed by an increase in investments in foreign startups, could be capturing a broad uptick in international orientation instead of our proposed mechanisms. We examine this possibility through a pair of placebo tests.

First, we used investments in other foreign countries besides India as the DV. If our results are explained by a general trend towards internationalization, *ties to Indian immigrants* should positively correlate with investments in non-Indian countries. The most common foreign destinations for U.S. VCs in our sample, other than India, are China (822 investments) and the United Kingdom (221 investments). But as shown in Table 9, we find no significant association between ties to Indian individuals (firs- or later-generation) and future investments in other countries.

Second, we assessed the effect of ties to entrepreneurs from other foreign countries on VC firms' investments and performance in India. Ties to non-Indians would affect VC's activities in India if they reflect a broad push towards internationalization, but not if the mechanism has to do with obtaining relevant knowledge and connections in India. We focused on ties to Chinese and Latin American entrepreneurs because they represent significant immigrant populations in the U.S. and their names are sufficiently distinct

to be identified using *forebears.io*. Using the same approach we used to identify Indians, we identified 440 surnames most common in China and 461 most common in Latin America (we included all countries in Central and South America where the primary language is not English). We then collected information on the individuals' job titles and tenure at the focal startup, retaining those who were founders or CEOs when the firm received investment from the VC firm of interest.[2] The results from using *ties to Chinese entrepreneurs* are summarized in table 10, whereas those for *ties to Latin American entrepreneurs* are in table 11. We find no meaningful impact of ties to Chinese and Latin American entrepreneurs on the number or success of subsequent investments in Indian startups ($p > 0.65$ in all cases).

*** TABLES 9, 10 AND 11 HERE ***

Systematic differences between first- and later-generation entrepreneurs. Differences between first- and later-generation immigrants in the value of their knowledge and connections are at the core of some of our arguments and results. One concern is that first-generation immigrants could be 'positively selected' because of superior capabilities, credentials, or other qualities that make them simultaneously more attractive to VCs in the U.S. and more likely to lead the same VCs to make better investments in India (other than through knowledge and connections in their homelands). To investigate this possibility, we explore the backgrounds of the first- and later-generation Indian immigrant entrepreneurs and the attributes of the startups with which they are associated in our sample.

We focus first on educational background, which is known to influence VC investment (Woolley, 2019). First- and later-generation Indian entrepreneurs are, statistically, equally likely to have an MBA (19% vs. 23%, respectively), but first-generation entrepreneurs are more likely to have a PhD (24% vs. 11%, $p < 0.001$). The PhD difference may proxy for a higher degree of technical skill, and VC firms with a stronger preference for such skills would favor first-generation Indians. But that would be an alternative explanation for our findings if that preference is also manifested in the Indian startups in which VCs invest. Yet the individuals involved in the Indian startups in our sample are substantially less likely to have a PhD (3%) than either first- or later-generation immigrant founders in the U.S. ($p < 0.001$ in both cases). These facts are not consistent with a preference for founders with PhDs as the underlying explanation for our results.

[2] We are unable to use the country in which ethnic Chinese and Latin American individuals completed their undergraduate studies to distinguish between first- and later-generation immigrants. The immigration dynamics for foreign students in the U.S. from the relevant countries are different than those for Indians.

Perhaps VCs prefer startups with strong technical capabilities, and first-generation immigrants are more likely to be associated with them. But we find no difference in the number of (eventually successful) patents filed by startups at the time of VC investment across firms with first- vs. later-generation Indians (6.2 vs. 5.5. patents, respectively, $p = 0.33$). We also find no systematic differences in the industries in which these startups operate (not shown but available upon request). In combination, these comparisons assuage the concern of 'positive selection' among first-generation immigrants. Further, any unmeasured differences between the two groups of Indians do not account for several hypothesized results that rely on differences among only the first-generation Indian immigrants to which U.S. VCs are tied.

We also carried out many other robustness tests. We measured investments in India based on 3- and 7-year windows instead of the 5-year window used in the main results. We captured ties to Indian immigrants as a proportion of the firm's US investments rather than a count. We used two alternative measures of the level of domestic competition: the number of active investors in the firms preferred sector in the U.S., and the CAGR in the number of active investors in this sector. We also carried out a range of other tests to examine the sensitivity of the conclusions to changes in the measurement of key variables or model specifications. None of these changes materially altered our findings. A detailed description of each robustness test and its results are available in the online appendix.

DISCUSSION

We began by identifying cross-border VC as puzzling, partly because it represents a deviation from the time-honored benefits of investing locally, and partly because of the substantial variation across firms in the extent, geography, and success of their foreign investments. The explanation we have offered addresses both aspects of the puzzle in a simple manner. VC firms seem to continue to rely on local networks, but seeding those networks with ties to immigrant entrepreneurs extends the geography of the opportunity sets they consider. Because such seeding is idiosyncratic, different firms end up forming ties to immigrants at different rates and from different homelands, which explains the heterogeneity behind our initial question.

Our study shows that ties to immigrant entrepreneurs provide benefits consistent with the strategic consideration of how those ties will factor into VC firms' ability to obtain a high-quality, proprietary deal flow. Two novel aspects of the paper in that regard are the results pertaining to performance (H4) and domestic competition (H3). Previous work has generally argued, but not demonstrated, that ties to immigrants can be valuable sources of information about foreign investment opportunities. We empirically show that this

is the case, and that ties formed both before and after making the focal foreign investment provide distinct value. The competition-related results further show that ties to immigrants are not equally valuable at all times, even for the same firm. Rather, the level of local competition seems to play an important strategic role in determining *when* firms activate the information and connections provided by immigrants. This explanation is consistent with the notion that firms tend to prefer investing locally until nudged to consider other options. It also demonstrates a mechanism by which firms address the rising problem in the VC industry of securing access to a proprietary deal flow under intense competition (Nanda *et al.*, 2020).

Another crucial aspect of this study is the distinction between first- and later-generation immigrants (H2a). That test provides a novel insight into the mechanisms explaining how ties to immigrants influence firms. Only ties to first-generation immigrants are potent enough to influence firms' strategic investments abroad—not those to later-generation immigrants of the same nationality. This rules out alternative explanations, including ethnic homophily or simply drawing a firm's attention to a foreign market. Rather, it shows that immigrants need to provide valuable knowledge, connections, or other resources to influence firms' choices. The test based on individuals' regional origins (H2b) play a similar role. We note that prior work on immigration in strategy has generally not made use of multi-generational differences across immigrants—which may be valuable to understand how different generations play different roles in firms.

We emphasize the importance of the multi-generation issue by offering an intriguing post-hoc finding. In our analyses, we control for the number of managers in the VC firm of the same ethnicity as the immigrants to which the firm is tied. But beyond just being a relevant control, does the presence of co-ethnic managers affect how much VC firms benefit from ties to immigrant entrepreneurs? Table A3 of the appendix shows that there is no significant interaction between ties to Indian immigrants and the number of Indian VC partners of any generation (first or later). But an interesting picture emerges when distinguishing between first- and later-generation Indian VC managers. While the number of later-generation Indian VC managers *enhances* the positive effect of ties to Indian immigrants on subsequent investments in India, the number of first-generation Indian immigrant VC managers *diminishes* the positive effect of ties to Indian immigrants. A linear model shows concordant results, except that the negative interaction is no longer significant. The consistent result is that ties to Indian immigrants are especially influential the more later-generation Indian managers in the VC firm.

This suggests an interesting distinction between first- vs. later-generation immigrants as "senders" vs. "receivers" of information. Expectedly, first-generation immigrants are more influential as senders than later-generation immigrants. As later generations assimilate, their direct knowledge of and connections to the homeland fade. But their affinity for the home country appears to have important implications for their behavior in other roles (such as partners in a VC firm) in which they act as receivers of the knowledge and connections that subsequent waves of co-ethnic, first-generation immigrants bring. An intriguing implication is that *multi-generational* transnational immigrant networks (vs. simply transnational) may be particularly important to activate ethnic ties that facilitate cross-border investment (see Levitt, 2001).

Our study also speaks to the dynamics of venture capital networks (Hallen, 2008; Hochberg *et al.*, 2010) and their effects on inclusion. The identity of the individuals in which VC firms invest can trigger a self-reinforcing cycle: entrepreneurs receiving investment today provide connections to those receiving investment tomorrow. Because homophily is a defining feature of most social networks, the lack of diversity in the investments of prominent VC firms may in part be a product of this process of network propagation (Brooks *et al.*, 2014; Kanze *et al.*, 2018). Seeding VC networks with ties to founders from different backgrounds may be an effective way to trigger a move towards investments in a more diverse pool of startups and geographies. Our study focuses on individuals of different nationalities, but similar mechanisms may operate with other aspects of entrepreneurs' backgrounds, including race and gender.

With regards to policy, much has been made of the contribution that immigrant entrepreneurs make to the economy of the receiving country (see Kerr, 2018; Wadhwa *et al.*, 2007) but less is known about their contributions to the sending country. In contrast to the brain drain concern, this study provides evidence of a (long-term) "capital gain" in the form of venture capital, which may help young firms in the sending country grow and investors in the receiving country allocate capital more broadly and efficiently than before. Perhaps migration can, under certain circumstances, create a cross-national ecosystem of entrepreneurship. Additional research should assess the net benefit for both the receiving and the sending economies.

The principal empirical challenge in this study is the possibility of unobserved selection mechanisms, as mentioned earlier. We took extensive steps to rule out the most salient of these concerns, but selection problems will not be fully resolved without a truly random mechanism by which VC firms establish ties to immigrant entrepreneurs. For instance, immigrants (first- or later-generation) may be different than the "average" founder in unobservable ways, which may bias our estimates in the performance regressions.

Further, our results most likely have boundary conditions. For instance, our study focuses on a pair of countries with idiosyncratic institutional environments and a unique historical relationship. The Indian educational system has played a significant role in creating strong IT talent exchanges between the U.S. and India, and that probably underpins some of the effects we find. Variation in institutional factors may lead to different effects for other country pairs, which we hope future work can explore.

Despite these limitations, we have offered a simple but powerful explanation for the rapid and heterogeneous growth of cross-border investments by VC firms, highlighting the strategic benefits of VC firms' ties to immigrant entrepreneurs. Beyond the application to the VC industry specifically, our study is relevant for organizational scholars, managers, and policy makers seeking to understand how migration affects cross-border investment, entrepreneurship, and economic growth.

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Figure 1a: Investments in India

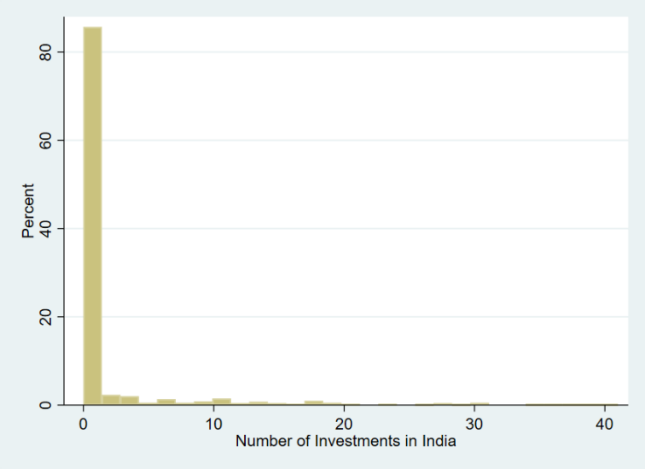
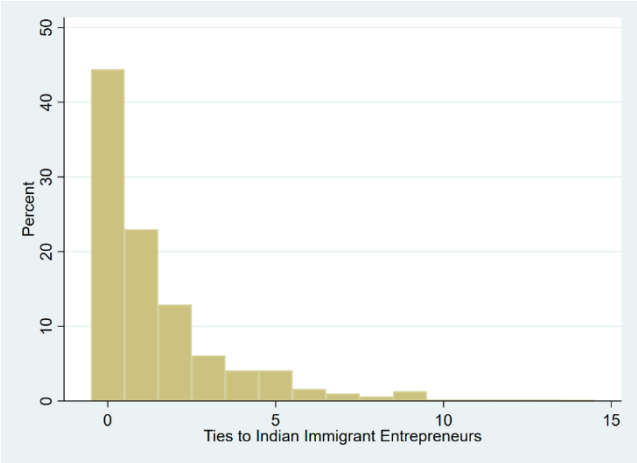
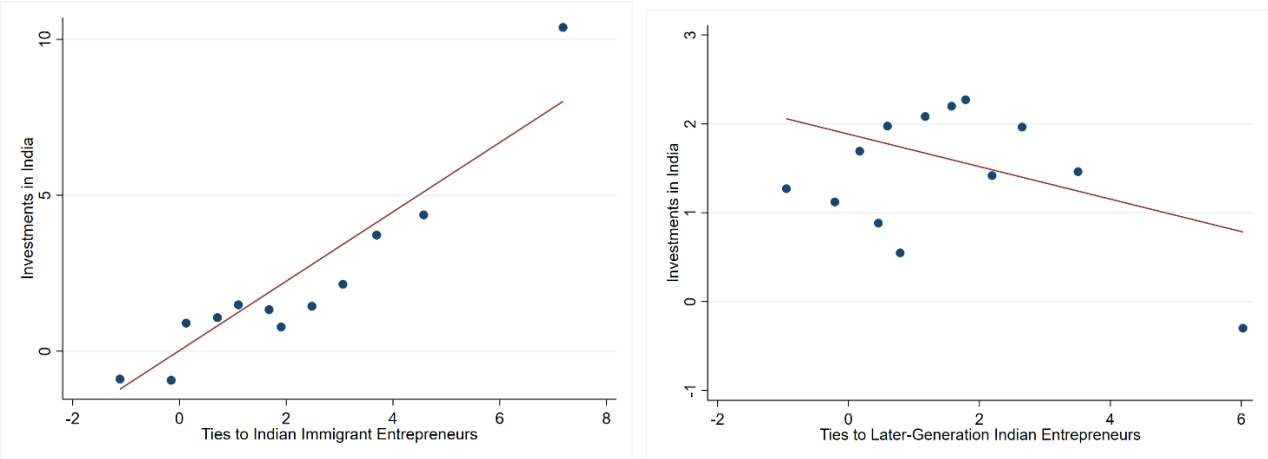


Figure 1b: Ties to Indian Immigrants



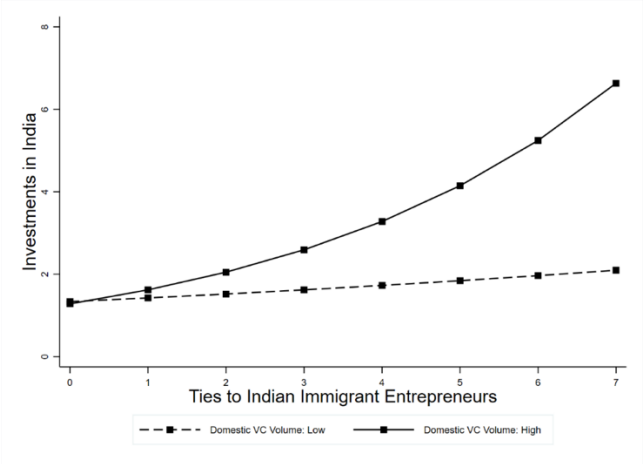
NOTE: Figure 1a shows the unconditional frequency of the number of investments in India by U.S. VC firms. The most common outcome is no investment, congruent with the known home bias and risk of foreign investment. Figure 1b shows the unconditional frequency of ties to Indian immigrant entrepreneurs by the U.S. VC firms in the sample between 2005-2014.

Figure 2: Ties to Indians and Subsequent Investments in India: First- vs. Later-Generation



NOTE: Ties to Indian immigrant entrepreneurs on LEFT, ties to later-generation Indian entrepreneurs on RIGHT. In each binscatter plot we control for the other X-axis variable given their correlation (e.g. we control for ties to later-generation Indians in the left plot, and vice versa). No other controls included in these plots.

Figure 3: Ties to Indian Immigrants X Domestic VC Volume in Firm's Preferred Sector



NOTE: Each point with a square marker indicates that the marginal effect of *ties to Indian immigrants* is significantly different ($p < 0.05$) across conditions of high vs. low domestic competition (90th vs. 10th percentile) at the specific number of *ties to Indian immigrants*. Note that the test is not based on the difference between the predicted values (vertical axis) shown on the graph but on the difference in the marginal effects (i.e. the slopes) at specific values of *ties to Indian immigrants* along the horizontal axis.

Table 1: Control Variables

(All time varying, measured as of the focal year unless otherwise explained)

	Control Variable	**Measurement**	**Reason for Inclusion**
1	Indian immigrant VC managers	Number of VC firm's managers who are first-generation Indian immigrants (Indian name plus undergraduate degree from an Indian institution).	A firm with more Indian managers may be better connected with and invest more in Indians in the U.S., while also being more likely to invest in India to begin with.
2	Later-generation Indian VC managers	Number of VC firm's managers who are later-generation Indian immigrants (i.e. Indian name but undergraduate degree from a U.S. institution).	Similar reasoning as above.
3	Local Indian-born Population	Number of Indian born people in the Metropolitan Statistical Area (MSA) of the VC firm's HQ.	A larger Indian population could affect the firm's exposure to Indian networks of entrepreneurs locally and the incidence, and performance of investments in India (Hernandez, 2014).
4	Prior investments in India	Number of Investments in India made by the focal VC firm in the three preceding years. (Bias could arise from the inclusion of a lagged DV in a panel regression with fixed effects. Our estimates are robust to the exclusion of this control variable.)	Experience in India affects the firms' future investments in the country. It may also affect the process by which the firm develops connections that lead to investments in startups led by Indian immigrants in the U.S.

5	Office in India	Binary variable indicating whether the firm has an office in India.	The presence of a local office has a direct link to the firm's commitment to India. Such an office and the connections resulting from it could be the source of U.S. investments in startups led by Indian immigrants.
6	India-focused fund	Binary variable indicating whether the VC firm has a fund, active in the focal year, specifically targeted to investments in India.	A firm with a fund of this nature is more likely to make investments in India. It may also be related to its propensity to invest in startups with Indian immigrants in the U.S.
7	International fund	Binary variable indicating whether the firm has a fund, active in the focal year, targeting international investments (i.e. outside the U.S.)	A more general version of the above: a more internationally focused fund may enable investments in India, and the creation of such a fund may also be related to local ties to immigrants of all nationalities.
8	Number of foreign investments	Number of investments made by the VC firm outside the U.S. in the focal year (not including investments in India)	Captures the firm's international orientation, which could relate to its investment in foreign countries (such as India) and its predilection to invest in foreign individuals within the U.S.
9	Number of U.S. investments	Number of investments made by the VC firm within the U.S.	Captures how actively the firm is making local investments. Affects the firm's capacity to take on new investments, both in the U.S. and abroad.
10	Proximity of U.S. investments	Proportion of the firm's U.S. investments in the focal year made in startups located in the same 2-digit zip code as the VC firm's HQ.	Reflects the firm's emphasis on geographically proximate (vs. distant) investments.
11	Fraction of investments in IT	Proportion of the total investments made by the VC firm, in the preceding five years, in startups operating in the information technology (IT) sector.	Given the prominent role of Indians in the IT sector (in the U.S. and globally), and the likelihood that a substantial proportion of Indian startups operate in this sector, a VC firm's focus on this sector could indicate a sector-specific selection related to both the outcome and explanatory variables of interest.
12	Total India VC in preferred sector	Total amount of VC investment (in USD billions) in India in the industry sector in which the firm made most investments in the focal year. Akin to *total US VC in preferred sector* (see text).	Reflects the level of interest and competition in in the firm's primary target VC sector in India, which could affect to the firm's choice to invest in India (and the investment outcome). Further, if Indians generally display particular skill in that sector, the measure could relate to the firm's investments in Indian immigrants in the U.S.

Table 2: Summary Statistics and Correlations

	Variable	Mean	SD	Min	Max	1	2	3	4	5	6	7
1	Investments in India	1.6	5.0	0	41	1.00						
2	Ties to Indians (any gen)	2.8	3.4	0	22	0.39	1.00					
3	Ties to Indian Immigrants	1.5	2.2	0	14	0.46	0.89	1.00				
4	Ties to Later Gen. Indians	1.2	1.8	0	12	0.18	0.83	0.49	1.00			
5	Indian VC Managers (any gen.)	0.8	1.1	0	5	0.32	0.43	0.42	0.32	1.00		
6	Indian Immigrant VC Managers	0.3	0.6	0	3	0.18	0.27	0.30	0.16	0.69	1.00	
7	Later Gen. Indian VC Managers	0.5	0.8	0	5	0.29	0.38	0.34	0.31	0.84	0.18	1.00
8	Local Indian-born pop. (x100k)	81.9	69.7	0	341.6	0.11	0.10	0.03	0.15	0.08	0.02	0.10
9	Prior India Investments	0.7	2.4	0	25	0.66	0.36	0.38	0.24	0.40	0.23	0.37
10	Office in India	0.1	0.3	0	1	0.63	0.37	0.40	0.22	0.49	0.25	0.47
11	India focused fund	0.0	0.1	0	1	0.23	0.09	0.10	0.05	0.10	-0.03	0.15
12	International focused fund	0.1	0.2	0	1	0.37	0.17	0.21	0.08	0.12	0.04	0.14
13	Number of Foreign Investments	2.7	5.3	0	70	0.52	0.33	0.35	0.21	0.13	0.01	0.16
14	Number of US Investments	28.1	16.7	1	113	0.27	0.63	0.55	0.53	0.29	0.15	0.29
15	Proximity of US Investments	0.4	0.2	0	1	0.12	0.30	0.29	0.22	0.12	0.13	0.06
16	Fraction of investments in IT	0.7	0.3	0	1	0.17	0.33	0.29	0.27	0.22	0.24	0.12
17	Tot. US VC in preferred sector ($B)	14.5	8.3	1.2	38.8	0.04	0.32	0.22	0.35	0.12	0.07	0.11
18	Tot. India VC in preferred sector($B)	0.6	0.9	0.0	3.4	0.00	0.26	0.18	0.27	0.10	0.07	0.08

	Variable	8	9	10	11	12	13	14	15	16	17	18
8	Local Indian-born pop. (x100k)	1.00										
9	Prior India Investments	0.14	1.00									
10	Office in India	0.16	0.69	1.00								
11	India focused fund	0.07	0.15	0.16	1.00							
12	International focused fund	0.22	0.23	0.31	0.23	1.00						
13	Number of Foreign Investments	0.13	0.52	0.41	0.15	0.45	1.00					
14	Number of US Investments	-0.06	0.29	0.24	0.06	0.08	0.34	1.00				
15	Proximity of US Investments	-0.06	0.11	0.08	0.00	0.05	0.13	0.15	1.00			
16	Fraction of investments in IT	0.01	0.14	0.14	-0.01	0.01	0.10	0.13	0.23	1.00		
17	Tot. US VC in preferred sector ($B)	0.15	0.15	0.06	0.01	0.03	0.18	0.13	0.17	0.30	1.00	
18	Tot. India VC in preferred sector($B)	0.14	0.11	0.03	-0.01	0.02	0.14	0.08	0.12	0.22	0.93	1.00

Based on 960 firm-year observations pertaining to 98 VC firms

Table 3: Ties to Indian Immigrants and Investments in India

	Model 1		Model 2		Model 3	
	Coef.	p val.	Coef.	p val.	Coef.	p val.
Ties to Indians (any gen.)			**0.0605**	**0.005**		
			(0.0216)			
Ties to Indian Immigrants					**0.0881**	**0.003**
					(0.0300)	
Ties to Later Gen. Indians					**-0.0240**	**0.571**
					(0.0424)	
Indian VC Managers (any gen.)	-0.0585	0.544	-0.0817	0.297		
	(0.0964)		(0.0784)			
Indian Immigrant VC Managers					-0.0223	0.895
					(0.1691)	
Later Gen. Indian VC Managers					-0.1036	0.358
					(0.1127)	
Local Indian-born pop.	0.0143	0.077	0.0167	0.056	0.0144	0.072
	(0.0081)		(0.0087)		(0.0080)	
Prior India Investments	0.0146	0.254	0.0230	0.112	0.0243	0.117
	(0.0128)		(0.0145)		(0.0155)	
Office in India	0.4072	0.018	0.2649	0.118	0.3132	0.096
	(0.1716)		(0.1693)		(0.1881)	
India focused fund	0.1314	0.343	0.1787	0.120	0.2189	0.241
	(0.1386)		(0.1150)		(0.1868)	
International focused fund	0.6954	0.102	0.8471	0.051	0.8300	0.050
	(0.4255)		(0.4336)		(0.4227)	
Number of Foreign Investments	0.0010	0.898	0.0025	0.625	0.0022	0.667
	(0.0076)		(0.0050)		(0.0051)	
Number of US Investments	0.0083	0.378	-0.0006	0.949	0.0023	0.804
	(0.0095)		(0.0098)		(0.0091)	
Proximity of US Investments	-0.7160	0.299	-1.0520	0.107	-1.0936	0.072
	(0.6895)		(0.6526)		(0.6072)	
Fraction of investments in IT	-0.0130	0.985	0.1174	0.855	0.1789	0.794
	(0.6737)		(0.6433)		(0.6851)	
Tot. US VC in preferred sector ($B)	0.0654	0.297	0.0525	0.362	0.0622	0.272
	(0.0628)		(0.0575)		(0.0566)	
Tot. India VC in preferred sector($B)	-0.2672	0.604	-0.2126	0.658	-0.2483	0.597
	(0.5145)		(0.4796)		(0.4695)	
Firm Fixed Effects	Y		Y		Y	
Year Fixed Effects	Y		Y		Y	
Num. Observations	960		960		960	
Log-likelihood	-545.6		-537.3		-533.3	
Pseudo-R2	0.497		0.504		0.508	

Estimates from negative binomial models with firm and year dummies. Standard errors are clustered by VC firm. DV is a count of investments in India during the five-year window following the focal year. *Ties to Indians (any generation)* is the number of ties to individuals of Indian ethnicity formed through investing in their startups in the U.S. *Ties to Indian immigrants* is the subset of these that are first-generation Indian immigrants, and *ties to later-generation Indians* is the subset native to the United States (i.e. second- or later-generation immigrants). Similar nomenclature applies with respect to VC managers.

A Wald test shows that the difference between *ties to Indian immigrants* and *ties to later-generation Indians* in model 3 is statistically significant (p = 0.036).

Table 4: Ties to Indian Immigrants from Different Regions and Investments in India

	Model 4		Model 5		Model 6		Model 7	
	Bangalore		Bangalore		Mumbai		Mumbai	
	Coef.	p val.	Coef.	p val.	Coef.	p val.	Coef.	p val.
Ties to Indian Immigrants	0.1005	0.001			0.0463	0.116		
	(0.0299)				(0.0295)			
Ties to Indian Immigrants (Bangalore)			**0.2334**	**0.000**			**0.0480**	**0.340**
			(0.0521)				**(0.0503)**	
Ties to Indian Immigrants (Mumbai)			**0.0344**	**0.494**			**0.1540**	**0.005**
			(0.0504)				**(0.0542)**	
Ties to Indian Immigrants (Other regions)			**0.0855**	**0.006**			**-0.0782**	**0.078**
			(0.0309)				**(0.0444)**	
Num. Observations	960		960		960		960	

All models include the controls listed in table 1 as well as firm and year fixed effects. Estimates from negative binomial models with firm and year dummies. Standard errors are clustered by VC firm. DV in models 4 and 5 is the number of investments in startups located in Bangalore during the five-year window following the focal year. In models 6 and 7 the DV is the equivalent for Mumbai. *Ties to Indian immigrants (Bangalore)* is a count of connections to immigrants from Southern India established by investing in their startups in the U.S. *Ties to Indian immigrants (Mumbai)* is the equivalent for immigrants from Western India, and *Ties to Indian immigrants (other regions)* is the equivalent for immigrants from other parts of India. See the text for a more complete explanation of how we determine immigrants' regional origins.

Wald tests based on model 5 show that *ties to Indian immigrants (Bangalore)* is different to both *ties to Indian immigrants (Mumbai)* ($p < 0.001$) and *ties to Indian immigrants (other regions)* ($p = 0.002$). Similarly, Wald tests based on model 7 show that *ties to Indian immigrants (Mumbai)* is different from both *ties to Indian immigrants (Bangalore)* ($p = 0.038$) and *ties to Indian immigrants (other regions)* ($p < 0.001$)

Table 5: Ties to Indian Immigrants X Domestic Competition and Investments in India

	Negative Binomial				Linear	
	Model 8		Model 9		Model 10	
	Coef.	p val.	Coef.	p val.	Coef.	p val.
Ties to Indian Immigrants	0.0888	0.004	0.0060	0.908	-0.0531	0.718
	(0.0307)		(0.0517)		(0.1467)	
Tot. US VC in preferred sector ($B)	0.0603	0.281	0.0285	0.620	-0.0131	0.386
	(0.0559)		(0.0575)		(0.0151)	
Ties to Indian Immigrants. x Tot. US VC in preferred sector ($B)			**0.0035**	**0.011**	**0.0180**	**0.051**
			(0.0014)		**(0.0091)**	
Num. Observations	960		960		960	

All models include the controls listed in table 1 as well as firm and year fixed effects. Estimates in models 8 and 9 are from negative binomial models. Estimates in model 10 are from OLS models (which are consistent but less efficient) included to aid with interpreting the magnitude of the interaction coefficients. Standard errors are clustered by VC firm. The interaction effect from model 9 is plotted in figure 3. *Total US VC in preferred sector* is the total VC invested in the industry sector where focal firm made most of its investments in the focal year. See previous tables for the definitions of other key variables.

Table 6: Ties to Indian Immigrants and Performance of Investments in India

	Within-portfolio		Cox Proportional Hazards model			
	Model 11		Model 12		Model 13	
	Coef.	p val.	Coef.	p val.	Coef.	p val.
Ties to Indian Immigrants (pre-investment)	**0.0136**	**0.027**				
	(0.0059)					
Ties to Indian Immigrants (flow)			**2.0150**	**0.000**		
			(0.3496)			
Ties to Indian Immigrants (stock)					**1.1233**	**0.016**
					(0.0542)	
Ties to Later Gen. Indians (pre-investment)	-0.0030	0.749				
	(0.0094)					
Ties to Later Gen. Indians (flow)			0.5315	0.001		
			(0.0972)			
Ties to Later Gen. Indians (stock)					0.8641	0.160
					(0.0898)	
Indian Immigrant VC Managers	-0.0356	0.380	0.8206	0.594	0.9821	0.966
	(0.0400)		(0.3045)		(0.4189)	
Later Gen. Indian VC Managers	-0.0438	0.265	1.1859	0.734	1.9736	0.095
	(0.0387)		(0.5945)		(0.8031)	
Local Indian-born pop.	-0.0054	0.119	1.0177	0.000	1.0169	0.000
	(0.0034)		(0.0041)		(0.0035)	
Prior India Investments	0.0044	0.350	0.9131	0.277	0.9198	0.206
	(0.0047)		(0.0764)		(0.0608)	
Office in India	0.1296	0.025	0.2784	0.145	0.3699	0.170
	(0.0552)		(0.2440)		(0.2680)	
India focused fund	-0.0804	0.211	4.1426	0.194	1.2303	0.835
	(0.0631)		(4.5316)		(1.2222)	
International focused fund	-0.2094	0.133	0.4247	0.399	0.5563	0.541
	(0.1360)		(0.4308)		(0.5339)	
Number of Foreign Investments	-0.0003	0.710	1.0511	0.215	1.0858	0.072
	(0.0008)		(0.0423)		(0.0497)	
Number of US Investments	-0.0015	0.240	0.9946	0.669	0.9922	0.536
	(0.0013)		(0.0127)		(0.0126)	
Proximity of US Investments	0.2291	0.405	0.6462	0.869	2.2039	0.760
	(0.2717)		(1.7106)		(5.7028)	
Fraction of investments in IT	0.3877	0.414	5.6829	0.509	3.4179	0.532
	(0.4688)		(14.9346)		(6.7290)	
Tot. US VC in preferred sector ($B)	-0.0030	0.771	0.8244	0.457	0.9288	0.742
	(0.0102)		(0.2139)		(0.2081)	
Tot. India VC in preferred sector($B)	-0.0419	0.222	3.3087	0.461	0.6335	0.741
	(0.0337)		(5.3670)		(0.8762)	
Firm Fixed Effects	Y		-		-	
Year Fixed Effects	Y		-		-	
Num. Observations	354		1146		1146	
Log-likelihood	98.5		-64.2		-69.3	
Pseudo-R2	0.222		0.181		0.116	

Estimates in model 11 are from OLS models with firm and year fixed effects. Estimates in models 12 and 13 are from Cox proportional hazards models, with coefficients presented as hazard ratios. Standard errors are clustered by VC firm in all models. In model 11, *exit* is measured during the 5-year period following the focal investment and *ties to Indian immigrants* are counted only in the year before the investment. In model 12, *ties to Indian immigrants* are measured as a time varying 'flow' of new ties to Indian immigrants in the U.S. in each year after the focal investment in India. In model 13, *ties to Indian immigrants* are measured as a 'stock' of accumulated ties to Indian immigrants in the U.S. starting from the year before the focal investment in India. See the text for more details.

Table 7: Tests of Alternative Mechanisms – Number of Investments in India

	Model 14		Model 15		Model 16		Model 17	
	Investments in different industry sector (VEIC)		Investments in unrelated sectors (text-based analysis)		Investments in startups with no U.S. connections		Investments in early-stage startups	
	Coef.	p val.	Coef.	p val.	Coef.	p val.	Coef.	p val.
Ties to Indian Immigrants	**0.0831**	**0.007**	**0.0888**	**0.003**	**0.0615**	**0.016**	**0.0776**	**0.000**
	(0.0310)		**(0.0303)**		**(0.0254)**		**(0.0220)**	
Ties to Later Gen. Indians	-0.0123	0.758	-0.0033	0.934	-0.0110	0.753	-0.0191	0.654
	(0.0399)		(0.0399)		(0.0350)		(0.0427)	
Num. Observations	960		960		960		960	

All models include the controls listed in table 1 as well as firm and year fixed effects. Estimates from negative binomial models with firm and year dummies. Standard errors are clustered by VC firm. In model 14, the DV is a count of the number of investments made by the VC firm in Indian startups that operate in *different* industry sectors than the startups in the U.S. led by Indian immigrant entrepreneurs in which the VC firm invested previously, based on *VentureXpert*'s industry classification (VEIC). Model 15 is analogous to model 14 but categorizes industry similarity based on a text-analysis approach described in the appendix. In model 16, the DV is a count of the number of investments in startups in India whose entrepreneurs have no prior experience studying or working in the U.S. (i.e. non-returnees). In model 17, the DV is a count of the number of investments made by the focal VC firm in early-stage startups in India (those receiving their first round of venture capital funding).

Table 8: Tests of Alternative Mechanisms – Performance of Investments in India

	Model 18		Model 19		Model 20		Model 21	
DV: Liquidity Event (Within Portfolio)	Performance of startups in different industry sector (VEIC)		Performance of startups in unrelated sectors (text-based analysis)		Performance of startups with no US connections		Performance of early-stage startups	
	Coef.	p val.	Coef.	p val.	Coef.	p val.	Coef.	p val.
Ties to Indian Immigrants	**0.0125**	**0.036**	**0.0204**	**0.012**	**0.0156**	**0.022**	**0.0115**	**0.003**
	(0.0058)		**(0.0076)**		**(0.0065)**		**(0.0036)**	
Ties to Later Gen. Indians	-0.0091	0.392	-0.0002	0.992	-0.0060	0.586	0.0016	0.905
	(0.0105)		(0.0244)		(0.0109)		(0.0132)	
Num. Observations	317		229		264		241	

Estimates from OLS models with all controls listed in table 3 plus VC firm and year fixed effects. Standard errors are clustered by VC firm. In model 18, the sample consists of Indian startups that operate in *different* industry sectors than the startups in the U.S. led by Indian immigrant entrepreneurs in which the VC firm invested, based on *VentureXpert*'s industry classification (VEIC). Model 19 is analogous to model 18 but categorizes industry similarity based on a text-analysis approach described in the appendix. In model 20, the sample consists of startups in India whose entrepreneurs have no prior experience studying or working in the U.S. (i.e. non-returnees) In model 21, the sample only consists of early-stage startups in India (those receiving their first round of venture capital funding).

Table 9: Placebo Test - Investments in Other Countries

	Model 3 (repeated)		Model 3a		Model 3b	
DV: Investments in	**India**		**China**		**United Kingdom**	
	Coef.	**p val.**	**Coef.**	**p val.**	**Coef.**	**p val.**
Ties to Indian Immigrants	**0.0881**	**0.003**	**0.0053**	**0.892**	**0.0101**	**0.609**
	(0.0300)		**(0.0391)**		**(0.0197)**	
Ties to Later Gen. Indians	-0.0240	0.571	-0.0545	0.238	0.0197	0.498
	(0.0424)		(0.0462)		(0.0291)	
Num. Observations	960		960		960	

Estimates from negative binomial models with all controls included (see table 1 for list) plus firm and year dummies. Standard errors are clustered by VC firm. DV is a count of investments in the corresponding country during the five-year window following the focal year: in model 3 this is India (same as model 3 of Table 3), in model 3a it is China, and in model 3b it is the United Kingdom.

Table 10: Placebo Test - Ties to Chinese Entrepreneurs

DV ->	**Investments in India**				**Liquidity Event**			
	Model 22		**Model 23**		**Model 24**		**Model 25**	
	Coef.	**p val.**	**Coef.**	**p val.**	**Coef.**	**p val.**	**Coef.**	**p val.**
Ties to Chinese Entrepreneurs	0.0027	0.941	0.0048	0.884	-0.0028	0.656	-0.0015	0.824
	(0.0368)		(0.0328)		(0.0063)		(0.0069)	
Ties to Indian Immigrants			0.0880	0.004			0.0135	0.029
			(0.0302)				(0.0059)	
Ties to Later Gen. Indians			-0.0240	0.571			-0.0028	0.774
			(0.0423)				(0.0099)	
Num. Observations	960		960		354		354	

All models include the full set of controls (see table 1 for list) as well as firm and year fixed effects. Estimates in models 22 and 23 are from negative binomial models. Estimates in models 24 and 25 are from OLS models. Standard errors are clustered by VC firm. Ties to Chinese entrepreneurs is the number of ties to entrepreneurs based in the U.S. whose surnames are most common in China (see text for more detail).

Table 11: Placebo Test - Ties to Latin American Entrepreneurs

DV ->	**Investments in India**				**Liquidity Event**			
	Model 26		**Model 27**		**Model 28**		**Model 29**	
	Coef.	**p val.**	**Coef.**	**p val.**	**Coef.**	**p val.**	**Coef.**	**p val.**
Ties to Latin American Entrepreneurs	0.0042	0.923	-0.0096	0.803	-0.0096	0.379	-0.0090	0.439
	(0.0430)		(0.0384)		(0.0108)		(0.0115)	
Ties to Indian Immigrants			0.0886	0.003			0.0135	0.035
			(0.0302)				(0.0062)	
Ties to Later Gen. Indians			-0.0245	0.563			-0.0027	0.775
			(0.0424)				(0.0094)	
Num. Observations	960		960		354		354	

All models include the full set of controls (see table 1 for list) as well as firm and year fixed effects. Estimates in models 26 and 27 are from negative binomial models. Estimates in models 28 and 29 are from OLS models. Standard errors are clustered by VC firm. Ties to Latin American entrepreneurs is the number of ties to entrepreneurs based in the U.S. whose surnames are most common in Latin America (see text for more detail).