Are Immigrant Entrepreneurs Magnets for Foreign Investors?

Mahdi Eghbali
Arizona State University

Melanie Wallskog
Duke University

Livia Yi*
Boston College

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Immigrant entrepreneurs play a vital role in the US startup landscape, yet how they affect the financing of US-based startups is not well understood. Using rich data on equity financing deals in the US, we identify three key findings. First, immigrant entrepreneurs are disproportionately financed in their early stages by investors based outside the US. Consistent with homophily, this pattern is mainly driven by immigrant entrepreneurs receiving equity financing from investors in their home countries and holds when leveraging within-founder variation in having immigrant co-founders. Second, these homophilic investments are not justified by better performance. Immigrant-founded startups financed by international investors are less likely to successfully exit than their native counterparts. Finally, through this homophily, immigrant-founded startups attract international capital to native entrepreneurs based in the same city, leading to regional financing spillovers. To mitigate potential confounding factors such as local economic trends, we employ a shift-share instrument. Taken together, these findings suggest that immigrant entrepreneurs contribute to the US startup ecosystem by serving as magnets for foreign investors.

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I Introduction

The United States has a long history of being known as the land of opportunity where entrepreneurship is highly valued and creativity and invention are praised. Many immigrants have flocked to the US to start and grow their own businesses. These immigrant entrepreneurs are important members of the US startup landscape. Immigrants are more likely to start new businesses than natives (Azoulay et al. (2022)), and high-skill immigrants boost innovation (see, for example, Hunt and Gauthier-Loiselle (2010); Kerr and Lincoln (2010); Doran and Yoon (2020); Bernstein et al. (2022)). Furthermore, immigrant entrepreneurs may have positive productivity spillovers on native entrepreneurs, leading to increased regional entrepreneurship and entry by productive firms (Mahajan (2022); Guzman, Tareque, and Wang (2022)).

Yet, despite the substantial set of findings on the vital role of immigrant entrepreneurs in creating jobs, revitalizing communities, and fostering US entrepreneurship and innovation, few empirical studies have examined whether immigrant entrepreneurs can attract international capital through their networks, skills, and sharing of common culture and language. To address this gap, we gather a novel list of entrepreneurs, investors, and US-based startups with at least one private capital funding round from Crunchbase and supplement the data with founders' LinkedIn information. The rich data set allows us to study an area that has received relatively little attention: the potential of immigrant entrepreneurs to affect the startup landscape by serving as magnets for international capital. We shed light on the contribution of immigrant entrepreneurs to the US startup ecosystem by investigating their ability to attract foreign investors to themselves and to startups nearby.

We begin by demonstrating that immigrant entrepreneurs form startups that disproportionately receive early financing from investors outside of the US. The presence of at least one immigrant founder at a startup is associated with an 18 percentage point higher likelihood of receiving international financing compared with startups exclusively founded by native entrepreneurs in the same industry and city. Since only 26% of startups have international investors when they raise capital, this predicted increase amounts to a 69% increase in the likelihood of having international investment, relative to the mean. These findings are consistent with homophily — immigrants and international investors disproportionately work together.

Two distinct sources of variation allow us to rule out confounding factors, such as the unobserved heterogeneity in the quality of startups founded by immigrant and native entrepreneurs. We leverage cross-country variations in the origin of both founders and investors to show that immigrant founders are particularly likely to attract international capital from investors based in their home countries. This test is restrictive because any potentially unobserved difference (such as quality) would need to be country-specific. Additionally, we leverage within-founder variation in having immigrant co-founders using the subsample of native serial entrepreneurs. These entrepreneurs are significantly more likely to secure international financing when they have an immigrant entrepreneur in the founding team.

While there are a variety of reasons why this homophilic investment pattern may exist — international investors may feel able to trust immigrant founders more, which may be particularly important across long distances, or these individuals may simply already know each other or exist in the same networks — we argue that this homophily is not entirely driven by international investors' ability to identify promising startups led by immigrants from the same country. We find that immigrant-founded startups financed by international investors are less likely to successfully exit (IPO or be acquired) than native-founded startups that receive international financing.

Given that immigrant-founded startups appear to disproportionately attract international investment, do they benefit nearby startups founded by US-born, native entrepreneurs? If such financing spillovers exist, it would imply that homophilic investments affect not only the immigrant entrepreneurs themselves but also the broader entrepreneurial ecosystem. Indeed, when international capital flows to immigrant entrepreneurs in a city in a given year, there is an increased likelihood of international capital flowing to native entrepreneurs in the same city the following year. To establish causality, we leverage variations in the historical locations of migrants and the current-day country-specific flow of capital to US startups, constructing a time-varying, city-specific shift-share instrument. Using this instrument and within-city variations, we find that immigrant entrepreneurs receiving international capital affect the likelihood of native firms receiving *international* capital, but not the likelihood of native firms receiving *domestic* capital, in the same city the next year. This contrast provides evidence for financing spillovers and rules out the possibility that we are solely capturing time-varying city economic trends.

These results support the notion that immigrant entrepreneurs act as a catalyst for foreign investment in the US startup ecosystem, serving as magnets for international investors. Further investigating the mechanism driving the spillovers, we find suggestive evidence that the spillover stems from international investors' increased experience in the city. Conditioning on city-by-year fixed effects, native-founded startups receiving international capital are more likely to have investors who had previous investment experience in the city, relative to startups with immigrant founders. Thus, it is likely that international investors "enter" a city by initially investing in an immigrant-founded startup and subsequently branch out to other ventures.

The paper unfolds as follows. Section II reviews prior works on immigrant entrepreneurship. Section III describes the data, variables, and samples. Section IV studies the role of homophily in immigrant entrepreneurs' access to finance. Section V examines the possibility of regional spillovers of homophilic international capital to native entrepreneurs. Section VI concludes.

II Related literature

We contribute to a large body of research on immigrant entrepreneurs that explores the role and impact of immigrants on the US entrepreneurship ecosystem and job growth. This literature has largely focused on documenting the role of immigrants as frequent entrepreneurs and innovators in the U.S. For example, Azoulay et al. (2022) find that immigrants are more likely than natives to launch new startups and act as "job creators".[1] Similarly, Kerr and Lincoln (2010) find that immigrant worker growth as a result of an increase in H-1B admissions leads to increased innovation activities.[2]

Beyond documenting the disproportionate entrepreneurship and innovation rate amongst entrepreneurs, the literature has also studied spillovers from immigrant and immigrant entrepreneurs, namely in terms of productivity. Immigrant inflows can increase regional entrepreneurship and entry by productive firms, leading to job creation and economic growth (e.g., Guzman, Tareque, and Wang (2022), Mahajan (2022)). Several papers have leveraged immigration policy shocks to study how immigrants can be important employees for new businesses. Dimmock, Huang, and Weisbenner (2022) find that successfully hiring high-skill immigrant workers increases startups' likelihood of both successful raising of venture capital financing and successful exit via IPO or acquisition. Similarly, Gupta (2023) argues that a reduction in immigrant labor availability reduces startup entry.

We complement this literature by studying an understudied angle of spillovers: financing spillovers. The basis for potential financing spillovers from immigrant-founded startups to native-founded ones lies in the idea that immigrant entrepreneurs may uniquely attract and facilitate international private capital flows.[3]

[1] Similarly, Fairlie and Lofstrom (2015) find that the business formation rate per month among immigrants was 0.51% compared to 0.28% for natives from 2007 to 2011, according to the Current Population Survey.

[2] Furthermore, Bernstein et al. (2022) show that immigrants contribute significantly to innovation and economic growth in the US. Hunt and Gauthier-Loiselle (2010) find that an increase in immigrant college graduates' population share leads to an increase in patent output. Doran and Yoon (2020) explore the relationship between immigrant language similarity and its impact on innovation. Krol (2021) provides a review of the related literature that discusses the impact of immigrants on entrepreneurship, employment growth, and innovation.

[3] Malki, Uman, and Pittino (2020) highlight that immigrant entrepreneurs may face distinct challenges in raising capital relative

Not only may immigrant entrepreneurs share common networks, culture, and language with international investors, they may also allow international investors to learn about local conditions.[4] In this paper, we first document how immigrant entrepreneurs are disproportionately financed by international investors and then show that this homophily generates local spillovers to native entrepreneurs — immigrant entrepreneurs are magnets for foreign investors.

III Data

We use data on startups, founders, investors, and financing from Crunchbase, a platform that amasses data on innovative startups, which we supplement with information from LinkedIn. Here, we describe our main sample of analysis, our methods for identifying immigrant founders, our data for constructing the shift-share instrument, and the key startup outcome variables.

Sample We construct a sample of startups headquartered in the US who raise at least one round of private capital between 2000 and 2021 that appears in Crunchbase. For these startups, we collect detailed information from company and founder profiles, including information on headquarters location, leadership, funding rounds, investment types, investor locations, mergers and acquisitions, IPOs, education and work experience of founder and employees, and detailed descriptions of a company's products and industry.

For each of the startups in our sample, we study all equity rounds between 2000 and 2021; most deals happen after 2010, as shown in Figure I. Within each round, we observe information on the deal itself (i.e., date and money raised) as well as information on the investors involved, including their headquarters location, by which we classify international investors.[5] Given the information on investors, we aggregate our data to the startup-year level by aggregating across deals within a year (most startups only have at most one deal per year). In this way, we study whether a startup receives more money in a given year, as well as whether it receives any international capital — i.e., whether any of its deals involve an international investor.

Identifying Immigrant-Founded Startups We follow the method applied by Balachandran and Hernandez (2021) and label startup founders' home countries by identifying the country of their earliest available

to native entrepreneurs.

[4]In a flipped version of our story, Balachandran and Hernandez (2021) study a related phenomenon: they argue that U.S. venture capitalists are more likely to invest in startups in India if they invest in more Indian-founded startups based in the U.S.

[5]When several investors participate in a given funding round, we cannot identify the amount each investor invests; instead, we see the total money raised, pooled across all investors. We also do not always observe the money raised; in our main startup-year level sample, 22% of observations have non-missing information on money raised. Except when we look directly at money raised, all regressions include deals where the money raised is unknown.

education. For about half of our sample, Crunchbase provides information on founders' education. For the remaining half, we supplement this information with additional data from the founders' LinkedIn pages. We acquire two rounds of LinkedIn data for this purpose, covering both the 2017 and 2023 snapshots.[6] We describe how we link Crunchbase to Linkedin data in Data Appendix A.II.

This approach allows us to identify the education background of around 75% of founder-startup pairs in the full Crunchbase data. While education is an imperfect indicator for nationality, especially since some immigrants will attend their entire post-secondary education in the US, we attempt to maximize the accuracy of this indicator by taking the earliest listed education, such as high school or undergraduate degree.[7] We classify the country location for each school through a combination of location information from Crunchbase, university lists, and Google Maps searches. We capture at least some of the group of immigrants who attend postgraduate programs in the US — over a third of the founders we identify as immigrants based on their education attended school in at least two countries. Because we are unable to identify the home country of every founder, we restrict our analysis to startups with at least one founder for whom we identify a home country.

Summary Statistics Table I presents summary statistics for our main sample of startup-year pairs in which a startup receives any financing. Panel A describes the entire sample; 31% of startup-year pairs represent startups with at least one immigrant founder. Panel B and C break out the sample into native-only- and immigrant-founded startups, respectively. On average, immigrant-founded startups have founder teams that are 75% immigrants, 25% natives. Compared to native-founded firms, immigrant-founded firms have more founders, are more likely to raise international capital, and have more investors in a given year, on average; immigrant-founded firms are also more likely to raise more money, on average, but not necessarily more international money, conditional on raising any.

When immigrant-founded firms raise international capital, it often comes from their home country. Figure II presents the flows of deals from international investors to immigrant-founded firms.[8] The figure presents a striking pattern: when an international investor invests in an immigrant-founded firm, the startup is disproportionately likely to have been started by immigrants from the same country in which the investor

[6]The 2017 and 2023 snapshots are provided by Datahut and the Bright Initiative by Bright Data, respectively.

[7]Where possible, we take each founder's earliest dated degree; otherwise, we take their high school, or undergraduate degree, to be their earliest school. Where we do not observe degree types or complete date information, we take the last listed education, under the assumption that education is listed in reverse chronological order.

[8]The figure restricts to each investors' first deal in our data and restricts to startups with at least one immigrant founder.

is located. In the remainder of the paper, we explore the role for homophilic investment more systematically.

IV Are Investments Homophilic?

We begin by investigating whether investments are homophilic on the basis of home country: are immigrant-founded firms more likely to raise capital from international investors, especially from their home countries, than native-founded firms? We begin with several pieces of correlative evidence and then leverage within-founder variation across startups to alleviate concerns that matching with international investors reflects other omitted variables.

IV.1 Correlative Evidence

To test whether having immigrant founders are associated with an increase in the likelihood of raising international capital, we employ regression models with the following format:

$$\begin{aligned} \mathbb{1}\{\text{Has International Investor}\}_{it} = & \alpha + \beta \mathbb{1}\{\text{Has Immigrant Founder}\}_i \\ & + \eta_{\text{Year} \times \text{Founding Year}} + \lambda_{\text{Industry} \times \text{City}} + \gamma_{\text{Round}} + \varepsilon_{it}. \end{aligned} \tag{1}$$

We use i to represent a startup and t to represent a year. $\mathbb{1}\{\text{Has International Investor}\}_{it}$ is an indicator variable that takes the value of one if a startup receives investment from at least one international investor during a given year. Similarly, $\mathbb{1}\{\text{Has Immigrant Founder}\}_i$ denotes if a startup has at least one immigrant founder. Our primary coefficient of interest is β, which captures the difference in the likelihood of having an international investor for immigrant- versus native-founded startups.

We include several controls in order to compare similar startups. To account for time-varying investment trends for startups of different ages, we control for year-by-founding year fixed effects. Furthermore, we include industry-by-city fixed effects to account for unobserved industry characteristics in the city where the startup is founded. For instance, the tech industry in Silicon Valley may have a different investor base than the tech industry in Boston. We also control for round fixed effects to account for the possibility that international and domestic investors tend to participate in different rounds of financing. We also examine alternative model specifications with fewer fixed effects, yielding similar results. To address potential within-startup residual correlations, we cluster standard errors at the startup level.

We find that immigrant-founded startups are disproportionately likely to receive funding from international investors. The results are presented in Table II. Among startups that have received financing deals in a given year, those with at least one immigrant founder in their team are more likely to attract international investors compared to those without immigrant founders. This pattern holds when we compare startups founded in the same year and raising capital in the same year as well as those headquartered in the same city and producing in the same industries. The pattern is also economically meaningful: as shown in our preferred specification in Column (6), the presence of an immigrant founder at a startup predicts a 18.4 percentage point higher likelihood of receiving international financing. Since only 26% of startups have international investors when they raise capital, this predicted increase amounts to a 69% increase in the likelihood of having international investment, relative to the mean.

IV.2 Empirical Approach: Leveraging Cross-Country and Within-Founder Variation

Immigrant-founded firms may differ from native-founded firms in other dimensions that drive the observed differences in international capital raised. While we control for various fixed effects such as industry, city, and founding year, it is still possible that unobserved heterogeneity, rather than homophily, is driving our results. We use two approaches to address this concern.

IV.2.1 Cross-Country Variations

First, we leverage variations in the countries of origin of both immigrant founders and international capital. We ask whether the investment pattern is country-specific: is an immigrant-founded startup's higher likelihood of having international financing mostly driven by financing from investors headquartered in the founders' home countries? To this end, we estimate regression models of the following format for the top five non-US countries with the highest immigrant frequency in our sample, which are India, the United Kingdom, Canada, Israel, and France:

$$\begin{aligned}\mathbb{1}\{\text{Has International Investor from Country X}\}_{it} = & \alpha + \beta \mathbb{1}\{\text{Has Immigrant Founder}\}_i \\ & + \gamma \mathbb{1}\{\text{Has Immigrant Founder from Country X}\}_i \\ & + \eta_{\text{Year}\times\text{Founding Year}} + \lambda_{\text{Industry}\times\text{City}} + \gamma_{Round} + \varepsilon_{it}\end{aligned} \tag{2}$$

We present our findings in Table III. For all of the top five most common immigrant countries — India, the United Kingdom, Canada, Israel, and France — the connection between immigrant status and having capital from a particular country is largely driven by immigrants from that country. With the exception of capital from the UK and France, immigrants are *only* more likely to receive financing from investors from a given country compared to natives *if* they themselves are from that country. In the case of the UK and France, immigrants from countries other than these two are also more likely to attract investment capital from investors in these countries. However, the association is much larger for immigrants from the UK and France themselves. Again, the correlations are economically meaningful. For example, non-Israeli immigrants are no more likely to receive Israeli capital than natives, but Israeli immigrants' startups are 42.7 percentage points more likely to receive Israeli capital, compared to the average probability of around 2 percent. These results significantly alleviate concerns that the observed matching between international investors and immigrant founders is driven by unobserved differences other than homophily, as it would require not only systematic disparities between firms founded by immigrants and those founded by native entrepreneurs but also disparities between firms founded by immigrants from one country and those founded by immigrants from another country.

There are a variety of reasons why immigrant-founded firms may be particularly likely to receive capital from investors from their home country. For example, the investors and immigrants may belong to the same network — indeed, some of the startups likely started in the founders' home countries, where investors may have played an immediate role.[9] Alternatively, investors may be able to more efficiently vet startups founded by people with familiar backgrounds, or they may place greater trust in their ability to monitor same-country startups from afar. In Appendix Table A.I, we show that homophily effects can extend across country borders, depending on the cultural similarity between investors and founders. Startups founded by immigrants who are more culturally distant from international investors of a particular country are less likely to attract financing from investors in that country.[10] All these reasons indicate some form of homophily — a force that disproportionately connects immigrant-founded startups and international investors.

[9]Note that our measure of startup location is a fixed one based on the most recent information Crunchbase has collected; this means that some U.S.-based startups may have actually received some of their rounds of funding outside the U.S. However, we believe that at least some of the homophilic financing is taking place after a startup has located in the U.S. For example, in unreported results we confirm similar homophilic patterns for U.S.-based immigrant-founded startups whose first rounds of financing are with domestic investors; we believe that these startups were likely already in the U.S. for these first rounds and so subsequently also in the U.S. for future rounds.

[10]We use cultural distance metrics that account for information across five dimensions: demographics, culture, politics, infrastructure, and geography. Each dimension includes multiple sub-categories. For example, the "Demographics" dimension includes fields like income, language, education, race, and others. Data can be found from Objective Lists at `https://objectivelists.com/2023/02/18/country-similarity-index-distance-matrix/`.

IV.2.2 Within-Founder Variations

The investment patterns documented in Section IV also apply to different startups founded by the same entrepreneur. In this test, we restrict the sample of founders to native serial entrepreneurs who found multiple startups in our data and leverage variations in the composition of their founder teams — specifically, the presence of immigrant co-founders. This design allows us to control for time-invariant characteristics associated with a given founder that may also affect the startup's ability or desire to attract international financing.

We present the results in Table IV. Within a founder, his or her startup companies are around 7 percentage points more likely to have an international investor when they have an immigrant co-founder. This holds true while controlling for the same set of fixed effects as before, as well as fixed effects for the native founder, the total number of founders at each startup, and the native founders' past experience (i.e., how many prior startups the founder had). The results show a similar pattern when considering cross-country variations in the co-founder's and international investor's country of origin. For instance, within the native founder group, their startup is 17.9 percentage points more likely to have Israeli investors when they have an Israeli co-founder (see Appendix Table A.II).[11] We take these results as additional evidence that our observed patterns reflect true homophily between immigrants and international investors.

IV.3 Are Immigrant-Founded Firms Better Investments?

Despite the observed homophily, it raises the question of whether these investments are efficient. In other words, are immigrant-founded firms more economically attractive as investments, particularly for international investors, compared to other firms?

If immigrant-founded startups appear inherently more promising to all investors, these startups may be more likely to raise capital from international and domestic investors alike. We show that this is not the case in Table V, where we estimate model 1, replacing as the dependent variable an indicator for whether a startup has any deals in a given year where *all* investors are headquartered in the US. As the table shows, immigrant-founded firms are significantly less likely to raise capital in exclusively domestic investor deals. Note that most startups only have one deal per year (84% of startup-years involve only one year), so the fact that the coefficients in Table V are approximately negative the coefficient in the same specification in

[11] It is worth noting that the statistical significance of coefficient estimates is low for some countries, likely due to the rarity of specific founder country combinations.

Table II is not surprising. Regardless, this test demonstrates that, at least on average, it is not the case that immigrant-founded firms are simply raising more deals from both domestic and international investors alike.

Furthermore, international investors are not necessarily picking higher productivity startups when they invest in immigrant-founded firms. We study this in Table VI, where we test whether the international investors invest in startups that are more likely to raise *future* capital and successfully exit, particularly when they invest in immigrant-founded firms. Immigrant-founded startups that receive international investment may appear to be slightly more successful in terms of financing — Column (3) suggests that they are more likely to raise another deal of financing in the next 5 years. However, Columns (4) through (6) suggest that they are less likely to successfully exit (IPO or be acquired) than native-founded firms receiving international investment. The number of observations decreases across the columns as observations in the most recent years need to be excluded when calculating the outcome variables related to future performance.

Overall, these patterns are consistent with international investors not necessarily leveraging connections with immigrant-founded firms to find future superstars; instead, they may be more willing to take a chance on "worse"-looking startups whose founders share similar backgrounds to them. Note that our proxy for quality is not perfect — we only capture the likelihood of a successful exit but cannot observe the returns conditional on exit.

V Spillovers of Homophilic Investments to Native Entrepreneurs

Considering that immigrant-founded startups appear to disproportionately attract international investment, the question arises: do they have a positive impact on nearby native-founded startups? If financing spillovers exist, it would suggest that homophilic investments affect not only the immigrant entrepreneurs themselves but also the broader entrepreneurial ecosystems in their vicinity.

In this section, we investigate the extent of such financing spillovers stemming from homophilic international investments to benefit native entrepreneurs across startups based in the same city, based on the idea that an international investor who has "entered" a U.S. city to work with an immigrant-founded startup may subsequently expand their investments locally. We begin by presenting correlational evidence, and subsequently adopt a shift-share (Bartik) instrument approach to establish causality.

V.1 Correlative Evidence

We begin with correlative analysis at the startup level in which we ask how the capital source for fundraising startups depends on the presence of nearby immigrant-founded firms raising international capital. In Table VII, we study how the presence of immigrant-founded startups predicts how other startups located in the same city raise capital. We estimate regression models of the following forms, respectively in Columns (1) and (2):

$$\begin{aligned}\mathbb{1}\{\text{Has International Investor}\}_{it} =& \alpha + \beta\mathbb{1}\{\text{Has Immig Founder}\}_i \\ &+ \gamma\mathbb{1}\{\text{Has No Immig.}\}_i \times \text{Log (\# Immig Firms in City)}_{it} \\ &+ \delta\mathbb{1}\{\text{Has Immig.}\}_i \times \text{Log (\# Immig Firms in City)}_{it} \\ &+ \theta\text{Log (\# Firms in City)}_{it} \\ &+ \eta_{\text{Year}\times\text{Founding Year}} + \eta_{\text{Industry}\times\text{City}} + \eta_{\text{Round}} + \varepsilon_{it}\end{aligned} \tag{3}$$

and

$$\begin{aligned}\mathbb{1}\{\text{Has International Investor}\}_{it} =& \alpha + \beta\mathbb{1}\{\text{Has Immig Founder}\}_i \\ &+ \gamma\mathbb{1}\{\text{Has No Immig.}\}_i \times \text{Log (\# Immig Firms w/ Int'l Investors in City)}_{it} \\ &+ \delta\mathbb{1}\{\text{Has Immig.}\}_i \times \text{Log (\# Immig Firms w/ Int'l Investors in City)}_{it} \\ &+ \theta\text{Log (\# Firms in City)}_{it} \\ &+ \eta_{\text{Year}\times\text{Founding Year}} + \eta_{\text{Industry}\times\text{City}} + \eta_{\text{Round}} + \varepsilon_{it}\end{aligned} \tag{4}$$

In Column (1), we test whether the presence of more immigrant firms raising *any* capital predicts how other startups located in the city raise international capital. Once we control for selection into city-industry pairs (as well as control for round fixed effect and year-by-year founded patterns), we find no spillover effects on native-founded firms. In other words, the mere presence of more fundraising immigrant-founded firms within a city in a particular year does not predict international capital raising by other startups.

However, we see a different pattern once we focus on the presence of immigrant-founded firms receiving *international capital*: Column (2) studies how the presence of more immigrant-founded startups raising *international* capital predicts how other startups raise capital. Here, even with strict fixed effects, both native- and immigrant-founded firms are more likely to raise international capital when their local immigrant-founded startups are raising international capital. For native-founded firms, a 10% increase in the local stock of immigrant-founded firms receiving international capital predicts a 0.6 percentage point higher likelihood of raising international capital, a 3% increase relative to the mean.[12] These results suggest that the spillover effects are not driven by the mere presence of immigrant-founded firms, but rather those immigrant firms' ability to attract international financing. These patterns are consistent with true spillovers: once an international investor has invested in an immigrant-founded startup in a given city, they may choose to expand locally.

We note that using concurrent measures of exposure to study spillovers — i.e., asking whether more immigrant-founded firms today predicts more international capital for native-founded firms today — may be subject to endogeneity concerns in the presence of common shocks. If a given city becomes particularly popular for international investors in a given year for reasons unrelated to the presence of immigrant-founded startups (e.g., because of a new flight connection), our estimates in Columns (1) and (2) may be biased. To address this, in Columns (3) and (4) we adapt models (3) and (4) to study whether the presence of immigrant-founded startups in the city in the *previous year* predict international fundraising. We find similar, though attenuated results. In Column (4), we find that a 10% increase in immigrant-founded firms receiving international capital in the previous year predict that a native-founded firm is 0.1 percentage points more likely to raise international capital, a 1% increase relative to the mean. In our subsequent spillover analyses, we focus on these more conservative lagged measures of exposure.

Given that exposure to *internationally-financed* immigrant-founded firms appears to form the crux of any spillovers, we next turn to regional analyses and estimate the spillover effects at the city level. We aggregate data at the city-year level and investigate whether the presence of immigrant-founded startups with international investments in the previous year influences the likelihood that native-founded startups in the same city will attract international investors in the current year. In this way, we study extensive margin spillovers at the city level. The OLS regressions take the following form:

$$\mathbb{1}\{\text{Int Capital to Native Startup}\}_{ct} = \alpha + \beta \mathbb{1}\{\text{Int Capital to Immig Startup}\}_{c,t-1} + \eta_t + \lambda_c + \varepsilon_{ct}, \quad (5)$$

[12] In this sample, 21% of native-founded firms receive international capital.

$\mathbb{1}\{\text{Int Capital to Native Startup}\}_{ct}$ is an indicator variable for whether the city c has native-founded startups receiving international capital in year t, and $\mathbb{1}\{\text{Int Capital to Immig Startup}\}_{c,t-1}$ is an indicator variable for whether the city c has immigrant-founded startups receiving international capital in year t-1. The regressions include city fixed effects to control for time-invariant city features (such as proximity to universities and other innovation hubs). We also control for macroeconomic trends in venture capital and angel investments using year fixed effects.

Table VIII presents the results. Column (1) suggests that the presence of immigrant-founded startups raising international capital in a city in the previous year is associated with a 7 percentage point increase in the likelihood of native startups raising international capital in the current year. Although city and year fixed effects help address many potential confounding factors, it remains possible that the observed spillover patterns are influenced by city-specific, time-varying economic trends or common shocks. Indeed, when we replace the outcome variable with an indicator for whether native startups raise capital from US-based investors (a placebo test that should theoretically yield no significant relationship), we still find a positive association, although with significantly smaller magnitude and lower statistical significance. To address endogeneity concerns, we employ a shift-share (Bartik) approach to instrument the capacity of local immigrants to attract international capital, described in detail in Section V.2.

V.2 Empirical Approach: Bartik Instrument

In order to causally estimate financing spillovers to native entrepreneurs, we develop an instrument for the likelihood of local immigrants to raise international capital in a given year using a Bartik shift-share approach. The key idea of this instrument is to predict current financing flows from international investors to immigrant entrepreneurs in a given city by leveraging historical distributions of immigrants; given these distributions, we predict that a city that historically had a larger Chinese population, for example, will receive more Chinese money flowing to Chinese entrepreneurs when there are more Chinese-to-Chinese capital flows nationally in a given year.

To construct the instrument, we multiply "shares" and "shifts" to get a predicted dollar amount of investment flowing to immigrants from international investors in a city and then take logs. The relevant shares are the shares of migrants from an origin country residing in a specific city during the base year 1990, and the shift measures the total international capital inflows from particular countries in a given year. The instrument is defined as follows:

$$\log(Z_{ct}) = \log(\sum_{j \in Countries} p_{ct_0 j} m_{tj}), \tag{6}$$

where $p_{ct_0 j} = \frac{N_{ct_0 j}}{N_{t_0 j}}$ is the share of immigrants nationwide from country j that were in city c in year t_0. We measure it using the Census 5% sample of the 1990 Decennial Census, which captures the distribution of immigrants more than a decade prior to the start of our sample.[13] Note that we use the distributions of *immigrants* rather than specifically *immigrant entrepreneurs*; we predict that immigrant entrepreneurs are more likely to settle in cities with immigrant enclaves from their city — e.g., Cuban immigrant entrepreneurs may set up their businesses in Miami, which historically had a larger Cuban community. m_{tj} measures the national amount of money inflow from country j in year t to immigrant entrepreneurs from country j. We calculate $p_{ct_0 j}$ and m_{tj} separately for countries that appear frequently in our founder dataset: Australia, Canada, China, France, Germany, India, Iran, Israel, Italy, Russia, Spain, and UK, and group the remaining countries into one category. For this test, we restrict the sample to years after 2005 so that there are sufficient deals available to calculate country-specific investments when constructing the shift measure, m_{tj}.

The concept behind this shift-share instrument is that when international capital from country j flows to immigrant entrepreneurs from country j in the US, it may have a greater tendency to go to regions with historically significant shares of immigrants from country j. If we assume that the historical locations of migrants are unrelated to contemporary entrepreneurial financing conditions, this instrument will create variations in the likelihood of immigrants raising international capital that are more likely to be exogenous.

We estimate model 5 in which we instrument for the presence of immigrant entrepreneurs receiving international capital in a city using our Bartik shift-share instrument. We present both first and second stage results in Table IX. Column (1) shows that the first stage estimate is positive and statistically significant at the 1% level, with an F-statistic of 8.3. In this first stage, a doubling of predicted international money raised by immigrant-founded startups predicts a 1.2 percentage point increase in the likelihood of immigrants raising international capital in a city, a 16% increase relative to the unconditional mean of 7.2%.

When we turn to the second stage, Column (2) suggests that the presence of immigrant-founded star-

[13] We source the Decennial Census data via the American Community Survey (ACS) from IPUMS. The Census data provide immigrant counts at the Census PUMA geography level; we map these to cities using the 1990 PUMA-to-city crosswalks provided by the Missouri Census Data Center. In cases where a PUMA region is mapped to multiple cities, or a city is mapped to multiple PUMA regions, we describe our mapping approach in the Data Appendix A.II.

tups attracting international capital in the city during the previous year leads to an increased likelihood of *native*-founded startups in the city receiving international capital in the current year: cities with at least one immigrant-founded startups recently receiving international capital is 82.4 percentage points more likely to have at least one native-founded startup currently receiving international capital.

Note that the two-stage-least-square (2SLS) coefficient estimates are larger than the OLS estimates shown in Table VIII, although not statistically distinguishable due to large standard errors stemming from a relatively weak instrument. This discrepancy may stem from 2SLS capturing the local average treatment effect (LATE) for compliers (in our case, capital flow distributions solely driven by historical migrant locations), which may be notably different than the average treatment effect (ATE) in the OLS results. Nonetheless, the large standard errors prohibit a strong comparison here; instead, we take the positive 2SLS results as robust causal evidence of the presence of spillovers.

The exclusion restriction in the Bartik setting can be viewed as a restriction on the exogeneity of "shares" (Goldsmith-Pinkham, Sorkin, and Swift, 2020). Following this interpretation, the identifying assumption is that the historical locations of immigrants influence international capital flows to native entrepreneurs solely through the current international capital flows to immigrant entrepreneurs. While this assumption is inherently untestable, we provide evidence that the placebo regression yields a negative and statistically insignificant result in the 2SLS framework, in contrast to our findings in the OLS framework: Table IX Column (3) shows the presence of immigrant-founded startups receiving international capital in the city during the previous year does not predict a higher likelihood of native-founded startups in the city attracting *domestic* capital in the current year. In other words, our instrument does not appear to be a instrument for capital in general but is rather specific to international capital. This finding helps rule out the alternative explanation that the observed effect in Column (2) is driven by concurrent economic trends in the city.

V.3 Mechanism: International Investor's City Exposure

How do immigrant entrepreneurs facilitate the flow of international capital to nearby firms? From the perspective of investors, it is plausible that investing in a locally established immigrant-founded startup enables them to explore additional local opportunities, whether by gaining insights about the area, forming new connections, or simply having already paid the "entry cost" for a city — if an Indian investor already flies to Cincinnati occasionally to meet with an Indian-founded startup located there, they may naturally combine those trips with visiting other startups. If this hypothesis holds, startups without immigrant founders should be more likely to have international investors who are already ”experienced” in the city.

We test this hypothesis in Table X. Using deal-level data from Crunchbase, we restrict to the first time each startup-investor pair matches in order to assess the experience of the investor prior to the first deal with a given startup. We create an indicator for whether the investor had a prior deal in the same city in years preceding the current startup deal and then estimate how this investor experience varies for native- versus immigrant-founded startups. In this test, we can effectively control for time-varying city characteristics by conditioning on city-by-year fixed effects, allowing us to compare startups within the same city *and* year.

In the first two columns of Table X, we show that native-founded firms who receive international money are significantly more likely to have matched with an investor with prior experience in their city, relative to immigrant-founded firms. In these columns, the omitted base group consists of startups with immigrant founders, such that the coefficient on having an international investor captures the pattern for immigrant-founded firms: immigrant-founded startups that match with international investors are 10 percentage points *less likely* to have matched with an investor with experience in their city, compared to immigrant-founded startups receiving domestic capital — in other words, immigrant-founded startups are more likely to be an international investor's "entry point" to a city. In contrast, native-founded startups with international investors are 8 percentage points *more likely* to have matched with an investor with experience in their city, relative to immigrant-founded startups with international investors. These native-founded firms are more likely to be "follow-on" investments for international investors in a given city.

In the last two columns, we show that these patterns are particularly stark when we delineate between immigrants from the same versus different countries as their international investors. In these columns, the omitted base group consists of startups with immigrant founders that receive financing from investors from the same country of origin. These columns demonstrate that immigrant-founded firms are only more likely be their international investors' "entry points" to a city if they are from the same country. Immigrant-founded firms from different countries than their investors look more or less like native-founded firms: they similarly are likely to be matched to international investors who already have experience in their city.

Taken together, these results align with the idea of international investors initially "enter" a city by investing in an immigrant-founded firm from their country and subsequently expanding to other ventures. The Indian investor "pays" the cost to enter Cincinnati by matching with an Indian-founded startup in Cincinnati, and then gradually expands to invest in native- and British-founded firms, etc. In this way, immigrant entrepreneurs serve as magnets for international investors, first attracting capital to themselves and then to other startups nearby.

VI Conclusion

Immigrant-founded startups make significant contributions to the US economy. In this paper, we shed light on an understudied aspect of their impact on the entrepreneurial landscape: their ability to attract international equity investments and the broader impact of such investments on regional entrepreneurial financing dynamics. We find that immigrant-founded startups are more likely to secure international capital, particularly capital from their home countries, and this cannot be solely attributed to differences across immigrant and native entrepreneur-founded ventures. Moreover, by drawing international capital to themselves, immigrant-founded startups increase the overall presence of international capital in the region, creating positive financing spillover effects for nearby native entrepreneurs. In this way, immigrant-founded startups serve as important magnets for foreign investors.

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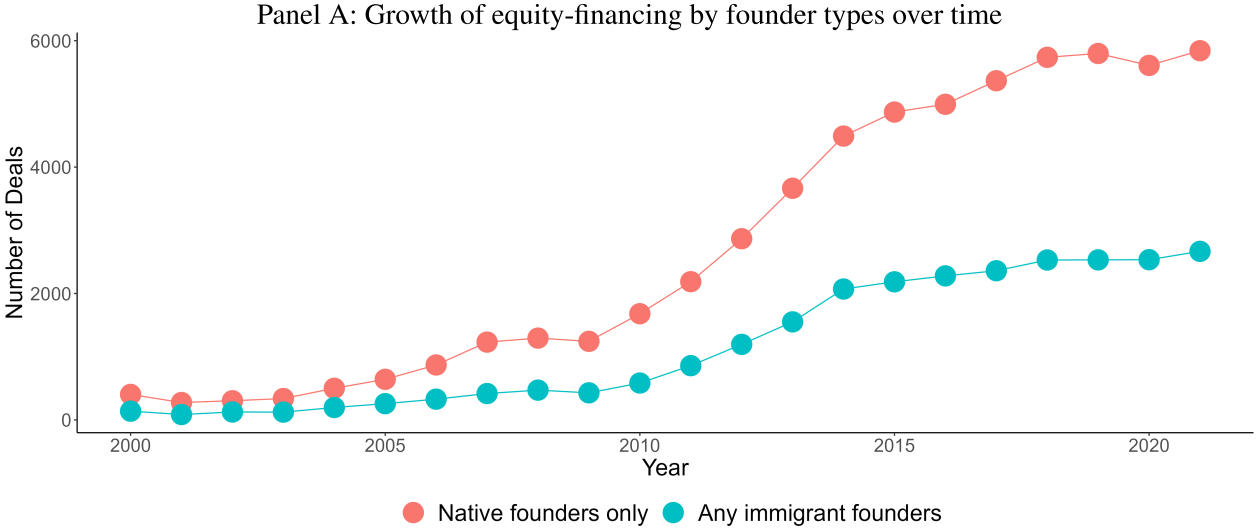
Figure I: Trends over time

In Panel A, we plot the number of equity-financed startups over time for those that do not have any immigrant founder (red line), and those that have at least one immigrant founder (green line), respectively. In Panel B, we plot the number of equity financing deals over time for the deals that do not involve any international investor (red line) and those that involve at least one international investor (green line), respectively.

Panel A: Growth of equity-financing by founder types over time



Panel B: Growth of equity financing by investors over time

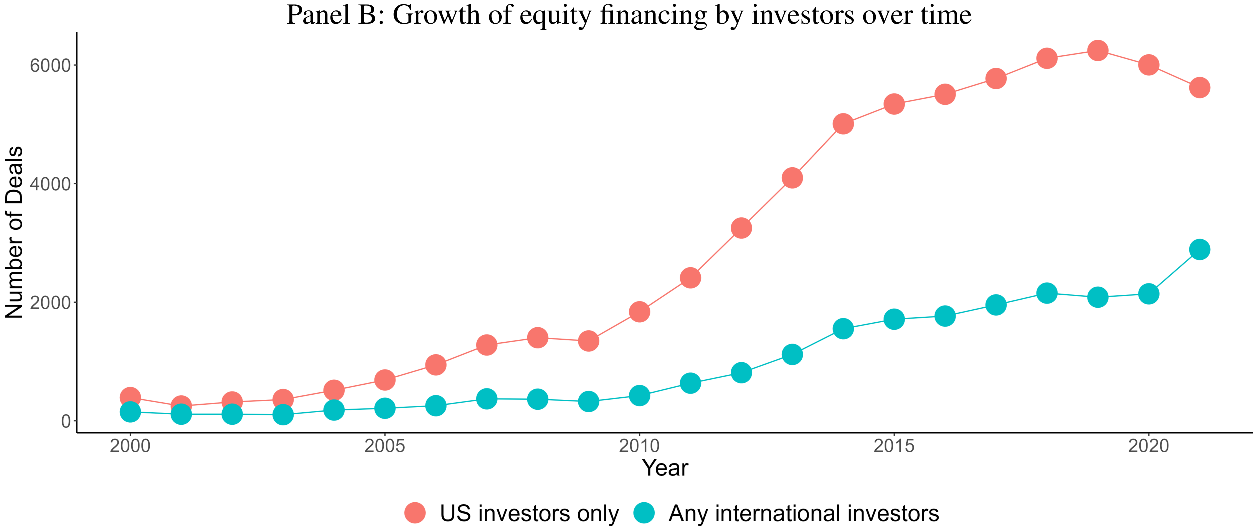


Figure II: Investors disproportionately target same-country startups for first deal

We present a Sankey diagram that shows the flows of deals from international investors to immigrant-founded firms by country. The sample is restricted to startups with at least one immigrant founder and each international investor's first deal; we plot only the most common immigrant countries in our data.

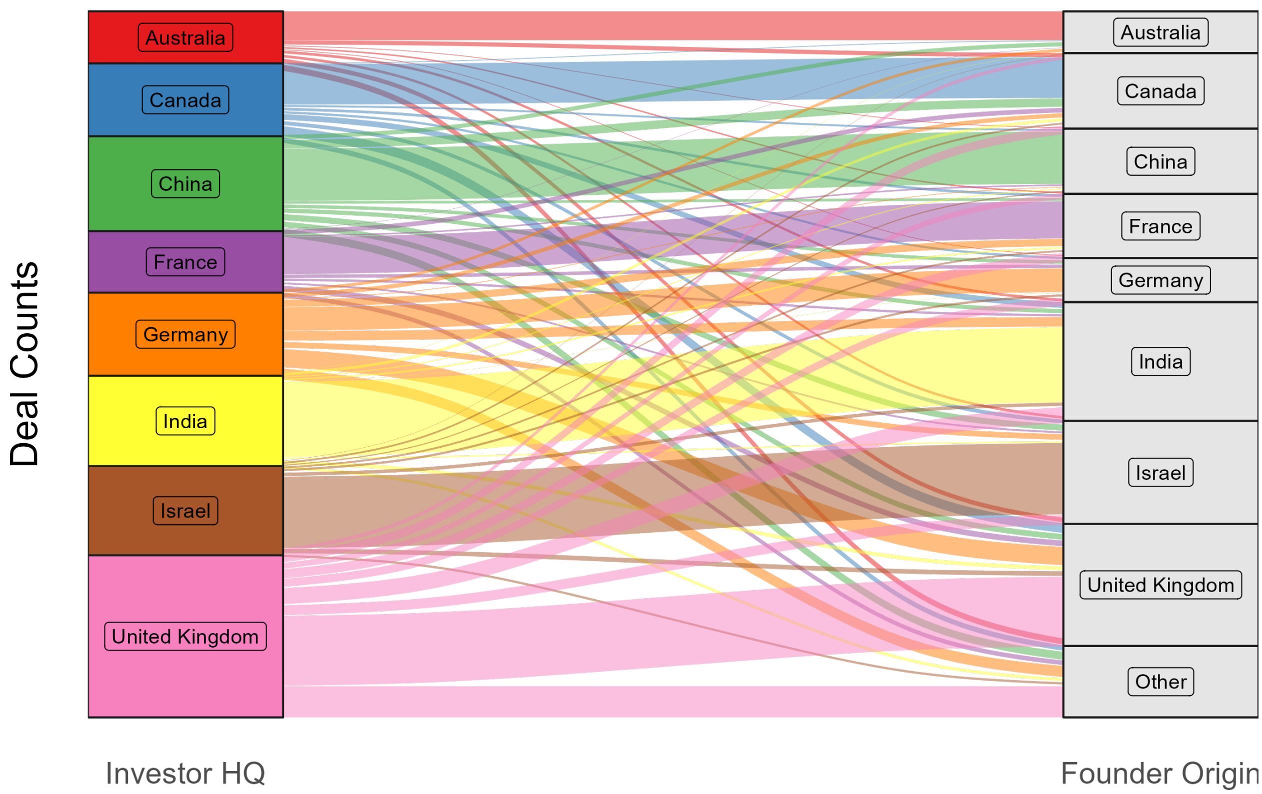


Table I: Summary Statistics

This table displays summary statistics for the sample of startup-year pairs in which a startup raises any equity financing. Panel A demonstrates the time span of our full sample and shows the share of startups with immigrant founders. Panel B shows characteristics of native-founded startups (i.e., those with no immigrants); Panel C shows characteristics for immigrant-founded startups (i.e., those with at least one immigrant).

Panel A: All startups

	Mean	SD	Median	Min	Max	N
Year	2015.47	4.53	2016.00	2000.00	2021.00	77,383
Year founded	2011.78	6.12	2013.00	1851.00	2021.00	77,383
Has Immigrant Founder	0.32	0.47	0.00	0.00	1.00	77,383

Panel B: Native-founded startups

	Mean	SD	Median	Min	Max	N
Year	2015.34	4.60	2016.00	2000.00	2021.00	52,726
Year founded	2011.45	6.33	2013.00	1851.00	2021.00	52,726
Total number of founders	2.05	1.02	2.00	1.00	20.00	52,726
Has any international investor in year	0.19	0.39	0.00	0.00	1.00	52,726
Number of investors in year	3.33	3.63	2.00	1.00	186.00	52,726
Log(money raised in year, billions)	-5.81	2.21	-5.55	-13.82	4.61	40,375
Log(money raised in deals w/ int'l investors in year, billions)	-4.82	1.97	-4.61	-13.82	4.61	8,447

Panel C: Immigrant-founded startups

	Mean	SD	Median	Min	Max	N
Year	2015.75	4.37	2017.00	2000.00	2021.00	24,657
Year founded	2012.48	5.59	2014.00	1851.00	2021.00	24,657
Share founders who are immigrants	0.74	0.28	1.00	0.13	1.00	24,657
Total number of founders	2.50	1.19	2.00	1.00	20.00	24,657
Has any international investor in year	0.41	0.49	0.00	0.00	1.00	24,657
Number of investors in year	3.58	3.64	2.00	1.00	96.00	24,657
Log(money raised in year, billions)	-5.66	2.15	-5.38	-13.82	2.19	19,328
Log(money raised in deals w/ int'l investors in year, billions)	-5.36	2.10	-5.12	-13.82	2.19	8,443

Table II: Immigrant-founded Startups Are More Likely to Raise International Capital

This table estimates models of Equation 1 and displays how international investment varies by the nationality of startups' founders. Startups with at least one immigrant founder are more likely to raise money in deals with at least one international investor. This pattern holds regardless of the inclusion of year, year-by-year founded, city, and city-by-industry fixed effects. Standard errors, adjusted for clustering at the firm level, are reported in parentheses. An observation is a startup-year pair, for years in which a given startup has any equity deals.

	$\mathbb{1}\{$Has International Investor$\}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Has Immigrant Founder	0.217***	0.215***	0.216***	0.185***	0.186***	0.184***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Year FE		X				
Year $\times$ Year Founded FE			X	X	X	X
City FE				X		
City $\times$ Industry FE					X	X
Round FE						X
Number of Obs.	77,383	77,383	77,383	77,383	77,383	77,383
R^2	0.06	0.07	0.08	0.12	0.19	0.21
Mean(Dep. Var.)	0.261	0.261	0.261	0.261	0.261	0.261
Mean(Indep. Var)	0.319	0.319	0.319	0.319	0.319	0.319

Table III: Homophily is Country-Specific

This table estimates models of Equation 2 and displays that the pattern shown in Table II is country-specific. Startups with immigrant founders are more likely to receive equity financing from international investors, predominantly those investors that are located in the *same* country their founders are from. This table shows this pattern for the most frequent international investor countries. Standard errors, adjusted for clustering at the firm level, are reported in parentheses. An observation is a startup-year pair, for years in which a given startup has any equity deals.

	$\mathbb{1}$\{Has International Investor from _____\}				
	India	United Kingdom	Canada	Israel	France
	(1)	(2)	(3)	(4)	(5)
Has Immigrant Founder	-0.002**	0.024***	-0.004**	-0.000	0.005***
	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
Has Founder from India	0.082***				
	(0.006)				
Has Founder from United Kingdom		0.069***			
		(0.009)			
Has Founder from Canada			0.092***		
			(0.008)		
Has Founder from Israel				0.427***	
				(0.015)	
Has Founder from France					0.185***
					(0.016)
Year × Year Founded FE	X	X	X	X	X
City × Industry FE	X	X	X	X	X
Round FE	X	X	X	X	X
Number of Obs.	77,383	77,383	77,383	77,383	77,383
R^2	0.14	0.12	0.12	0.37	0.13
Mean(Dep. Var.)	0.009	0.053	0.030	0.021	0.017
Mean(Has Founder from given country)	0.060	0.044	0.040	0.032	0.018

Table IV: Native Founders Receive International Financing When They Have Immigrant Co-founders

This table displays that the patterns shown in Table II hold within-native founder. Native founders with multiple startups are more likely to receive international capital *when* they have immigrant co-founders. This table adds various controls beyond those in previous table, including fixed effects for founder, number of founders (startup team size), number of firms founded by a founder, and order in which firms are founded. Standard errors, adjusted for clustering at the founder level, are reported in parentheses. An observation is a native founder-startup-year pair, for years in which a given startup has any equity deals.

	$\mathbb{1}\{$Has International Investor$\}$				
	(1)	(2)	(3)	(4)	(5)
Has Immigrant Founder	0.073***	0.071***	0.068***	0.068***	0.067***
	(0.011)	(0.017)	(0.018)	(0.018)	(0.017)
Year × Year Founded FE	X	X	X	X	X
City × Industry FE	X	X	X	X	X
Round FE	X	X	X	X	X
Founder FE		X	X	X	X
# Founders FE			X	X	X
# Firms FE				X	X
Firm Order FE					X
Number of Obs.	25,022	25,022	25,022	25,022	25,022
R^2	0.23	0.48	0.48	0.48	0.48
Mean(Dep. Var.)	0.242	0.242	0.242	0.242	0.242
Mean(Indep. Var)	0.171	0.171	0.171	0.171	0.171

Table V: Immigrant-founded Startups Are Less Likely to Have Deals Exclusively from US Investors

This table shows that immigrant-founded firms are not more likely than native-founded firms, on average, to raise capital from domestic investors. Startups with at least one immigrant founder are less likely than native-founded firms to have at least one deal in a given year where all investors involved are headquartered in the US. Standard errors, adjusted for clustering at the firm level, are reported in parentheses. An observation is a startup-year pair, for years in which a given startup has any equity deals.

	$\mathbb{1}\{$Has a Deal with Exclusively US Investors$\}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Has Immigrant Founder	-0.216***	-0.214***	-0.215***	-0.184***	-0.185***	-0.183***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Year FE		X				
Year × Year Founded FE			X	X	X	X
City FE				X		
City × Industry FE					X	X
Round FE						X
Number of Obs.	77,383	77,383	77,383	77,383	77,383	77,383
R^2	0.06	0.07	0.08	0.12	0.19	0.21
Mean(Dep. Var.)	0.734	0.734	0.734	0.734	0.734	0.734
Mean(Indep. Var)	0.319	0.319	0.319	0.319	0.319	0.319

Table VI: Homophilic Investment Is Not Correlated with Higher Exit Probability

This table shows that immigrant-founded startups financed by international investors are marginally more likely to raise money in the next 1, 3, and 5 years, but are less likely to successfully exit, measured using going public (IPO) or being acquired. The number of observations decreases across the columns as the observations in the most recent 1, 3, and 5 years are excluded when calculating the outcome variables. Standard errors, adjusted for clustering at the firm level, are reported in parentheses.

	$\mathbb{1}$\{Has Deal in ___\}			$\mathbb{1}$\{Exit in ___\}		
	1 Year	3 Year	5 Year	1 Year	3 Year	5 Year
	(1)	(2)	(3)	(4)	(5)	(6)
Has International Investor	-0.003	0.013*	0.008	0.010***	0.013**	0.019**
	(0.006)	(0.008)	(0.009)	(0.003)	(0.006)	(0.009)
Has Immigrant Founder	0.005	0.012*	0.010	-0.002	-0.006	-0.006
	(0.005)	(0.007)	(0.008)	(0.002)	(0.005)	(0.008)
Has International Investor × Has Immigrant Founder	0.007	0.013	0.023*	-0.012***	-0.028***	-0.045***
	(0.009)	(0.011)	(0.013)	(0.004)	(0.009)	(0.013)
Year × Year Founded FE	X	X	X	X	X	X
City × Industry FE	X	X	X	X	X	X
Round FE	X	X	X	X	X	X
Number of Obs.	67,690	52,492	38,433	67,690	52,492	38,433
R^2	0.10	0.12	0.14	0.12	0.16	0.22
Mean(Dep. Var.)	0.307	0.531	0.579	0.047	0.144	0.248
Mean(Indep. Var)	0.252	0.247	0.239	0.252	0.247	0.239

Table VII: International Capital Spills Over to Native Founders in Immigrant-Founded Startups' Cities

In this table we study how both currently and previously present immigrant-founded startups may attract international capital to a other startups in a city within the US. $\mathbb{1}\{$Has Immig.$\}$ equals one if a startup has at least one immigrant founder. $\mathbb{1}\{$Has No Immig.$\}$ equals one if a startup has no immigrant founder. Log {# of Immig startups in City} is the natural logarithm of the number of immigrant-entrepreneur-founded startups in a city receiving any financing in a given year; in columns 1 and 2, this is a concurrent measure, while in columns 3 and 4 it is lagged (i.e., the number from the previous year). Log {# of Immig startups w/ Int'l Investors in City} is the natural logarithm of the number of immigrant-entrepreneur-founded startups in a city that received international investment; in columns 1 and 2, this is a concurrent measure, while in columns 3 and 4 it is lagged (i.e., the number from the previous year). Standard errors, adjusted for clustering at the startup level, are reported in parentheses. An observation is a startup-year pair, for years in which a given startup has any equity deals.

	$\mathbb{1}\{$Has International Investor$\}$			
	Concurrent Exposure		Lagged Exposure	
	(1)	(2)	(3)	(4)
Has Immigrant Founder	0.141***	0.113***	0.149***	0.148***
	(0.016)	(0.011)	(0.015)	(0.011)
Has No Immig. X Log(# Immig Firms in City)	-0.002		0.009	
	(0.011)		(0.010)	
Has Immig. X Log(# Immig Firms in City)	0.011		0.020*	
	(0.012)		(0.010)	
Has No Immig. X Log(# Immig. Firms w/Int'l Investors in City)		0.063***		0.012**
		(0.006)		(0.005)
Has Immig. X Log(# Immig. Firms w/Int'l Investors in City)		0.086***		0.026***
		(0.006)		(0.006)
Year × Year Founded FE	X	X	X	X
City × Industry FE	X	X	X	X
Round FE	X	X	X	X
Log(# Firms in City)	X	X		
Lag Log(# Firms in City)			X	X
Number of Obs.	55,968	55,968	55,968	55,968
R^2	0.17	0.17	0.17	0.17

Table VIII: City-Level Spillovers: Correlative Evidence

This table estimates Equation 5 and studies whether immigrant-founded startups may attract international capital to native-founded startups in the same city. $\mathbb{1}\{$*Int Capital to Native Startup*$\}$ is an indicator variable for whether the city has native entrepreneur-founded startups receiving international capital in a given year. $\mathbb{1}\{$*Native Capital to Native Startup*$\}$ is an indicator variable for whether the city has native entrepreneur-founded startups receiving US-investor capital in a given year. $\mathbb{1}\{$*Int Capital to Immig Startup*$\}$ *(Lag)* is an indicator variable for whether the city has immigrant entrepreneur-founded startups receiving international capital in the prior year. Standard errors, adjusted for clustering at the city level, are reported in parentheses. An observation is a city-year.

	$\mathbb{1}\{$Int Capital to Native Startup$\}$	$\mathbb{1}\{$Native Capital to Native Startup$\}$
	(1)	(2)
I (Int Capital to Immig Startup) (Lag)	0.067^{***}	0.026^{**}
	(0.013)	(0.013)
City FE	X	X
Year FE	X	X
Number of Obs.	31,872	31,872
R^2	0.47	0.48
Mean(Dep. Var.)	0.072	0.199
Mean(Indep. Var.)	0.053	0.053

Table IX: 2SLS Estimations of City-Level Spillovers

This table uses a shift-share instrument in a 2SLS framework to study whether immigrant-founded startups may attract international capital to native-founded startups in the same city. The instrument, *Log Shift X Share*, is defined in Equation 6 and described in Section V.2. $\mathbb{1}\{$*Int Capital to Native Startup*$\}$ is an indicator variable for whether the city has native entrepreneur-founded startups receiving international capital in a given year. $\mathbb{1}\{$*Native Capital to Native Startup*$\}$ is an indicator variable for whether the city has native entrepreneur-founded startups receiving US-investor capital in a given year. $\mathbb{1}\{$*Int Capital to Immig Startup*$\}$ *(Lag)* is an indicator variable for whether the city has immigrant entrepreneur-founded startups receiving international capital in the prior year. Standard errors, adjusted for clustering at the city level, are reported in parentheses. An observation is a city-year.

	First Stage	Second Stage	
	$\mathbb{1}\{$Int Capital to Immig Startup$\}$ (Lag)	$\mathbb{1}\{$Int Capital to Native Startup$\}$	$\mathbb{1}\{$Native Capital to Native Startup$\}$ *(Placebo)*
	(1)	(2)	(3)
Log Shift X Share (Lag)	0.012***		
	(0.004)		
I (Int Capital to Immig Startup) (Lag)		0.824*	-0.579
		(0.447)	(0.679)
City FE	X	X	X
Year FE	X	X	X
Number of Obs.	31,872	31,872	31,872
Mean(Dep. Var.)	0.053	0.072	0.199
Mean(Indep. Var.)	-9.635	0.053	0.053

Table X: The Role of International Investors' Previous Experience in City

This table studies whether startups without immigrant founders are more likely to have international investors who are previously "experienced" in a city compared with startups with immigrant founders, and startups with immigrant founders working with investors from the same country. Standard errors, adjusted for clustering at the city level, are reported in parentheses. An observation is a startup-year.

	$\mathbb{1}$\{Experienced in City\}			
	(1)	(2)	(3)	(4)
No Immig Founder	0.003	0.003	-0.010	-0.011
	(0.005)	(0.005)	(0.007)	(0.007)
Has International Investor	-0.103***	-0.099***	-0.256***	-0.253***
	(0.007)	(0.007)	(0.013)	(0.014)
No Immig Founder × Has International Investor	0.076***	0.075***	0.230***	0.230***
	(0.009)	(0.009)	(0.014)	(0.015)
Immig Founder Diff Country			-0.028***	-0.028***
			(0.008)	(0.009)
Immig Founder Diff Country × Has International Investor			0.211***	0.213***
			(0.016)	(0.016)
Year × Year Founded FE	X	X	X	X
City × Industry FE	X	X	X	X
Round FE	X	X	X	X
City × Year FE		X		X
Number of Obs.	60,921	60,921	60,921	60,921
R^2	0.29	0.33	0.29	0.33
Mean(Dep. Var.)	0.609	0.609	0.609	0.609

A.I Appendix Tables and Figures

Table A.I: Homophily is Country-Specific But Also May Depend on Cultural Similarity

This table displays that the pattern shown in Table III may stretch beyond same-country pairs to countries with a higher degree of cultural similarity. Startups with immigrant founders are more likely to receive equity financing from international investors, predominantly those investors that are located in the *same* country their founders are from, but also from investors that are located in countries that are *culturally similar* to their home country. This table shows this pattern for the most frequent international investor countries. Standard errors, adjusted for clustering at the startup level, are reported in parentheses. An observation is a startup-year pair, for years in which a given startup has any equity deals. Cultural similarity is measured as a cultural distance bounded between 0 and 1, where a larger number indicates that countries are less similar. We source this measure from Objective Lists.

	$\mathbb{1}$\{Has International Investor from ____\}				
	India	United Kingdom	Canada	Israel	France
	(1)	(2)	(3)	(4)	(5)
Has Immigrant Founder	-0.010***	0.036***	0.007**	0.007***	0.008***
	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)
Has Founder from India	-0.025***				
	(0.009)				
Avg. Cultural Dist. to India	-0.207***				
	(0.022)				
Has Founder from United Kingdom		0.030***			
		(0.010)			
Avg. Cultural Dist. to UnitedKingdom		-0.113***			
		(0.018)			
Has Founder from Canada			0.075***		
			(0.009)		
Avg. Cultural Dist. to Canada			-0.047***		
			(0.010)		
Has Founder from Israel				0.232***	
				(0.028)	
Avg. Cultural Dist. to Israel				-0.389***	
				(0.046)	
Has Founder from France					0.153***
					(0.015)
Avg. Cultural Dist. to France					-0.097***
					(0.012)
Year × Year Founded FE	X	X	X	X	X
City × Industry FE	X	X	X	X	X
Round FE	X	X	X	X	X
Number of Obs.	77,261	77,261	77,261	77,261	77,261
R^2	0.15	0.12	0.12	0.38	0.13
Mean(Dep. Var.)	0.010	0.053	0.030	0.021	0.017
Mean(Has Founder from given country)	0.060	0.044	0.040	0.032	0.018

Table A.II: Native Founders Receive International Financing When They Have Immigrant Co-founders

This table displays that the patterns shown in Table III hold within-native founder. Native founders with multiple startups are more likely to receive international capital from a specific country when they have immigrant co-founders from that *same* country. Standard errors, adjusted for clustering at the founder level, are reported in parentheses. An observation is a native founder-startup-year pair, for years in which a given startup has any equity deals.

	$\mathbb{1}$\{Has International Investor from _____\}				
	India	United Kingdom	Canada	Israel	France
	(1)	(2)	(3)	(4)	(5)
Has Immigrant Founder	0.004	0.021*	0.001	-0.007	-0.001
	(0.003)	(0.012)	(0.007)	(0.005)	(0.004)
Has Founder from India	0.012				
	(0.008)				
Has Founder from United Kingdom		0.041			
		(0.027)			
Has Founder from Canada			0.019		
			(0.020)		
Has Founder from Israel				0.179***	
				(0.041)	
Has Founder from France					0.063***
					(0.024)
Year × Year Founded FE					
City × Industry FE	X	X	X	X	X
Round FE	X	X	X	X	X
Founder FE	X	X	X	X	X
# Founders FE	X	X	X	X	X
# Firms FE	X	X	X	X	X
Firm Order FE	X	X	X	X	X
Number of Obs.	25,022	25,022	25,022	25,022	25,022
R^2	0.45	0.40	0.40	0.50	0.44
Mean(Dep. Var.)	0.006	0.053	0.029	0.011	0.014
Mean(Indep. Var)	0.031	0.027	0.029	0.009	0.009

A.II Data Appendix

In this paper, we combine data from several sources, including Crunchbase, LinkedIn, and the 1990 Decennial Census. In this data appendix, we include details on how these data are matched together, as well as how we identify immigrant entrepreneurs.

A.II.1 Linking Crunchbase and LinkedIn Data

As discussed below in Section A.II.2, we use information on startup founders' education in order to classify immigrants. We combine several waves on LinkedIn data in order to increase our coverage of founders' education information. The first wave of data comes from Crunchbase itself (which we believe sources the data from LinkedIn). The second and third waves capture LinkedIn snapshots from 2017 and 2023, provided by Datahut and the Bright Initiative by Bright Data, respectively. In order to combine these data sources, we match our Crunchbase observations on founders to the other LinkedIn snapshots using LinkedIn profile URLs. In this section, we describe the steps involved in this linkage.

For both the 2017 and 2023 snapshots, as well as the Crunchbase data, we start by cleaning the LinkedIn profile URLs provided in each dataset in order to get a harmonized set of URLs. We restrict the URLs to shortened versions that following the format "linkedin.com/.../..." by stripping away prefixes (e.g., "www."), query strings, and other variations. [14]

After harmonizing the URLs, we proceed with exact matching the URLs across the datasets in order to fill in additional information for our Crunchbase founders' education.[15] For the 2017 snapshot, the education data is stored analogous to the Crunchbase data (i.e., separate columns for describing the timing and characteristics of each degree) and so is immediately ready for the processing described in the next section. For the 2023 snapshot, the education data is stored in structs that we parse in order to match the format of the 2017 snapshot and Crunchbase data.[16]

After linking the Crunchbase data on founders with the two additional waves of LinkedIn data, we have up to three sets of education histories for each founder. In the next section, we describe how we use these histories in order to classify immigrants.

[14] For example, we end up with something like: "linkedin.com/in/melanie-wallskog-0a09387b." In our replication package, this and future steps are enacted via the `short_url` function. We skip the minority of URLs that cannot be harmonized.

[15] In our replication package, we perform this match with parallel processing.

[16] In our replication package, this procedure is accomplished by the `expand_edu` function.

A.II.2 Identifying Founders' Home Countries

Given the education histories of each founder, we classify each founder in terms of their "home country," where this home country is the country of their earliest listed education. While education is an imperfect indicator for nationality, especially since some immigrants will attend their entire post-secondary education in the US, we attempt to maximize the accuracy of this indicator by taking the earliest listed education, such as high school or undergraduate degree.

In order to perform this classification, we first classify the country location for each degree listed on any education history (i.e., Crunchbase and the 2017 and 2023 snapshots of LinkedIn). Then, we identify each founder's earliest education; this degree's location defines the founder's nationality for our paper.

Classifying Locations of Degrees To classify locations of each degree in our education histories, we leverage several data sources:

1. Crunchbase itself contains some information on location for many schools.
2. We look up universities in a list of over 9,000 universities around the world with 2-letter country codes.[17]
3. We search for each school on Google Maps and take the country for the page source, where available.[18]
4. We search for each school on Google Maps and take the latitude and longitude from the source code; we then find the country based on these coordinates.[19]

If all these sources agree on a school's country, we take that country as the school's location. If there is disagreement across the sources, we prioritize the Crunchbase-based location and otherwise proceed in the following steps sequentially. First, if the school was perfectly matched to the universities list, we take the country from that list. Second, if the two Google Maps based methods agree and do not identify multiple countries, we take the country from the Maps search. Third, we manually fix some cases: for example, we fix cases where Google Maps identified a U.S. state as opposed to the U.S. as the location and we label

[17] We source this list from Github endSly/world-universities-csv, at `https://github.com/endSly/world-universities-csv/blob/master/world-universities.csv)`. We accessed this list May 22, 2022. We fuzzy match school names in our data to this list in the program `get_countries_fuzzy_name.py`.

[18] We conduct this search using the program `get_latlon_googe.py`.

[19] We conduct his process using the program `get_latlon_google.py` and `get_country_from_latlon.py`.

schools as being located in the U.S. if they include in their name a U.S. state (e.g., "University of North Carolina"). Finally, we harmonize the names of countries in order to match our list of investor headquarters countries in Crunchbase (e.g., we pool England, Scotland, Wales, and Great Britain to form the United Kingdom). At the end of this process, we are left with one country per school.[20]

Identifying Earliest Degree Once we have locations for schools, we label a founder's home country using the location of their earliest listed degree. If all schools in a founder's education history are located in the same country, we skip finding the founder's earliest degree and simply take that country as the founder's home country.[21] In cases where a founder has degrees listed in multiple countries, we identify this earliest listed degree in the following sequential procedure and then take the country of this degree; in this procedure, we only proceed to the next step if we still do not have an earliest degree for a founder.

1. Some founders have matriculation and/or graduation dates listed for degrees. We classify a degree's date as the matriculation date if available and the graduation date otherwise. If a founder has dates listed for all degrees, we take the earliest dated degree.

2. Some founders have degrees or schools listed that are high schools (i.e., contain the phrase "high school"). In this case, we take this as the earliest degree. If a founder has multiple high school degrees, we take the one with the earliest date, if all dates are available. (If a founder has multiple high school degrees with missing dates, we proceed to the next step.)

3. Many founders have degrees listed as bachelor's degrees (e.g., "BA"). In this case, we take this degree as the earliest degree. If a founder has multiple bachelor's degrees, we take the one with the earliest date, if all dates are available. (If a founder has multiple bachelor's degrees with missing dates, we proceed to the next step.)

4. For founders with multiple bachelor's degrees spread across multiple countries, with at least one missing date, we manually search the cases. (This is a small group of people, about 0.1% of the Crunchbase and 2017 snapshot-matched founders.) In many of these cases, it was clear that one of the listed bachelor's degrees was a partial-year study abroad program (for example, the study abroad

[20] The final classification procedure is available in `education_NEW_10032023.do`. We are not able to classify every school, especially in cases where school names are recorded in different alphabets.

[21] This is the case for the vast majority of founders — for the Crunchbase and 2017 snapshot data, over 90% of founders matched have only one country across all listed degrees.

program degree had the word "exchange" in the title, or the study abroad program was listed as starting and ending within a year). If this was clear, we took the other full undergraduate degree program as the earliest degree.

5. Finally, we assume (as is typical on LinkedIn) that degrees are listed in reverse chronological order (i.e., most recent degrees listed first). We take the last listed degree as the earliest.

Given this earliest degree, we have our home country for each founder. We implement the above procedure in parallel two sets of education histories. First, we pool the education histories from Crunchbase and the 2017 LinkedIn snapshot and identify an earliest degree for each founder. Second, we separately identify an earliest degree in the 2023 LinkedIn snapshot.[22] We prioritize the home country based on the first set of histories and only utilize the 2023 snapshot where it provides new information of education (i.e., where a founder has added new education information to their LinkedIn profile). Note that we are not able to find the education and home country for every founder, and so our analysis in this paper is restricted to startups with at least one founder with "known" home country, given our imputation.

A.II.3 Matching PUMAs and Cities in the American Community Survey (ACS)

In Section V.2, we construct a shift-share Bartik instrument for the flow of international capital to immigrant-founded startups based on historical immigrant distributions sourced from the 1990 Decennial Census sample provided in the American Community Survey (ACS) data section of IPUMS. This demographic microdata provides geographic information on immigrants, but the data is only available at the Census Public Use Microdata Area (PUMA) level, rather than the city level.[23]

We source a PUMA-city crosswalk for 1990 from the Missouri Census Data Center, which we then use to map the Census data on immigrant distributions to city-level estimates of 1990 immigrant populations. However, PUMAs are neither strict subsets nor supersets of cities; instead, they are non-overlapping statistical geographic areas within states.[24] Indeed, in the PUMA-city crosswalk, some cities match to multiple PUMAs, and some PUMAs match to multiple cities. In cases where a PUMA region is mapped to multiple cities, or a city is mapped to multiple PUMA regions, we distribute the PUMAs' immigrant population to

[22]We separate the 2023 snapshot because it was a late addition the project and we preferred to preserve our initial classification in order to be consistent with past drafts of the paper.

[23]Note that PUMAs are combined with state indicators to actually identify distinct areas; we refer to them just as PUMAs here to simplify the language, but every calculation at the PUMA level is actually at the state-PUMA level.

[24]See https://www.census.gov/programs-surveys/geography/guidance/geo-areas/pumas.html for details.

cities in the following procedure meant to distribute PUMA population counts to cities according to approximate city size.

First, we count the number of times each city appears in the PUMA-city crosswalk; we assume that cities that appear more frequently are larger. Second, we sum up this number across cities for each PUMA to get a measure of the mass of cities in each PUMA. Third, for each city, we allocate the immigrant population (from a specific country) in a given PUMA according to shares given by the number of times the city appears in the crosswalk (i.e., from the first step) divided by the total number of times all of the cities in the PUMA appear in the crosswalk (i.e., from the second step). Finally, we sum these population counts across PUMAs within a city.