Native-Immigrant Entrepreneurial Synergies*

Zhao Jin† Amir Kermani‡ Timothy McQuade§

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Abstract

We examine the performance of startups co-founded by immigrant and native teams. Leveraging unique data linking startups to founders' and employees' employment and education histories, we find native-migrant teams outperform native-only and migrant-only teams. Native-migrant startups have larger employment three years after founding, are more likely to secure funding, access larger funding rounds, and achieve more successful exits. An instrumental variables strategy based on native shares in university-degree programs confirms native-migrant teams are larger and more likely to receive funding. Superior access to diverse labor pools, successful VCs, and expanded product markets are key factors in driving native-migrant outperformance.

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†Cheung Kong Graduate School of Business, jinzhao@ckgsb.edu.cn

‡UC Berkeley, Haas School of Business and NBER, kermani@berkeley.edu

§UC Berkeley, Haas School of Business and NBER, tmcquade@berkeley.edu

1 Introduction

Immigrants are a major source of entrepreneurial activity in the United States, driving both new firm creation and innovation. Indeed, previous research has shown that approximately one quarter of new employer businesses in the United States are started by immigrants (Kerr and Kerr 2016; Azoulay et al. 2022). Bernstein et al. (2022) report that immigrants have been responsible for 23% of US patents produced since 1976, despite constituting only 16% of the total US-based inventor population. As Chodavadia et al. (2024) notes, as of 2022 the four most valuable private, venture-backed US companies had immigrant founders, as well as three of the most valuable public companies globally. On the intensive margin, Brown et al. (2019) and Lee et al. (2023) show that immigrant-founded firms in the United States are more innovative than native-founded firms, while Ostrovsky and Picot (2021) documents similar results for Canada.

Moreover, immigrant entrepreneurs often do not form new companies in isolation. Indeed, new startups with immigrant founders often have native co-founders as well. Previous research on inventors has shown that immigrants generate significant positive productivity spillover effects on US-born inventors, as measured by patenting (Bernstein et al. 2022). In this paper, we evaluate whether startups with immigrant and native co-founders outperform startups with only native or migrant founders. We first leverage new data linking startups to the immigration status and career / educational histories of the founders so as to document stylized facts regarding the relative performance of startups by the demographic composition of their founding team. We then develop an instrumental variables (IV) strategy exploiting plausibly exogenous variation in the opportunity of US-born entrepreneurs to co-found companies with immigrants to assess the causality of immigrant-native outperformance. Finally, we present evidence on the potential mechanisms underlying such outperformance.

Our research combines data from Revelio Labs and Crunchbase. The Crunchbase database provides comprehensive information on startups, including its founding date, funding history, investors, acquisition, and IPO status. This data is linked to Revelio Labs, which sources data from the LinkedIn profiles of more than 850 million individuals in over 200 countries. This data provides detailed information on an individual's employment history, educational background, occupation, and skillset. The richness of this information allows us to identify the founders of the startups in Crunchbase. Following Amanzadeh, Kermani, and McQuade (2024), we identify immigrant entrepreneurs and workers in the United States using information on the initial country that appears in the LinkedIn profile, based on either education or job position.

We first present basic descriptive facts on migrant entrepreneurial activity in the United States and the collaboration of migrant entrepreneurs with US-born entrepreneurs. First, the migrant share of US-based entrepreneurs has been steadily rising, from 12% in 2000 to 27% in 2022. During this period, the origin countries with the most migrant entrepreneurs are, in rank order, India, the UK, and Canada. Relative to the total number of startups in that industry, migrant entrepreneurs are most active in artificial intelligence, blockchain and cryptocurrency, and data and analytics. Startups featuring both US-born and migrant entrepreneurs are common. Approximately 50 percent of entrepreneurs from the UK and Canada co-found a company with a US-born entrepreneur. The propensity for Indians is less, but still approximately one-third of Indian entrepreneurs co-found with a native.

Startups founded by native-migrant teams appear to outperform startups founded solely by natives or migrants. Three years after inception, startups with native-migrant teams are 20% larger than native-only startups as measured by employment. While migrant-only startups also outperform native-only startups, the effect is only 15%. Native-migrant startups are larger than migrant-only startups by 8% three years after inception. Native-migrant startups are also significantly more likely to receive funding than native-only startups, and raise substantially more capital than both native-only and migrant-only startups. Startups with native-migrant teams are also more likely to be acquired and more likely to exit through an IPO than either native-only or migrant-only startups.

We next investigate potential mechanisms that could underlie the increased growth and funding access of startups founded by native-migrant teams, relative to both native-only and migrant-only startups. We consider three such mechanisms. These are access to a more diverse, highly skilled labor pool, access to investor capital, and access to product markets. We find that native-migrant startups hire 27.1% more migrant employees than native-only startups, while hiring slightly less migrant-workers than migrant-only startups. Using internal and external promotions as a proxy for labor quality, we additionally find that native-migrant startups hire better quality workers than both native-only and migrant-only firms. Disaggregating further, we find that native-migrant startups hire significantly higher quality migrant workers than native-only startups, while they hire native workers of comparable quality. In contrast, migrant-only startups hire native workers of significantly lower quality than both native-migrant and native-only startups, suggesting that native-migrant teams are particularly effective in sourcing high-quality labor from both the native and immigrant pools.

Turning to capital access, startups founded by native-migrant teams are 7.7% more likely to be funded by non-US investors relative to startups without a migrant co-founder. Migrant-only firms are slightly more likely to access foreign VC funding than native-migrant startups. We next proxy for VC quality by number of deals and number of successful exits. We find that native-migrant teams disproportionately access capital from VC funds with more deals and more successful exits, relative to both native-only and migrant-only teams. Similar to our results on labor market access, we additionally find that native-migrant startups access capital from higher quality foreign VCs than native-only startups. Native-migrant startups also receive capital from higher quality domestic VCs than native-only startups, while migrant-only firms are actually less successful than native-only firms in accessing capital from top domestic VCs.

The last potential mechanism we investigate is product market access. Since we cannot directly observe the markets in which a startup sells products or provides services, we proxy for this outcome using patents filed in both the United States and outside the United States. Native-migrant firms have 117% more total granted patents than migrant-only firms and 28.4% more granted patents than native-only firms. Turning to the filing location, migrant-only firms are less likely to be granted a US patent than native-only firms, while they exhibit a similar propensity to receive a foreign patent. In contrast, native-migrant teams are more likely to receive both US and non-US patents than both migrant-only and native-only startups.

Several heterogeneity tests provide additional support for these underlying mechanisms. We first show that the migrant-native outperformance is more pronounced in those industries and states which make heavy use of both native labor and migrant labor from the founder's origin country. Similarly, we show that the migrant-native outperformance is more pronounced in those industries and states that heavily source both domestic VC capital as well as VC capital from the founder's origin country. Both of theses results support the idea that migrant-native teams facilitate expanded access to high-quality labor pools and sources of capital. We also show that migrant-native teams feature a greater diversity of skills, such as combining technical skills with sales/marketing experience, and feature greater ethnic diversity. However, additional heterogeneity tests suggest that migrant-native outperformance is not driven by these characteristics of migrant-native entrepreneurial teams.

The causal interpretation of our baseline empirical results is challenged by selection concerns. That is, the outperformance of native-migrant startups could be driven by high-productivity entrepreneurs endogenously sorting into native-migrant teams, rather than productivity benefits created by the native-migrant combination itself. To address this concern, we develop an instrumental variables (IV) strategy exploiting plausibly exogenous variation in the ability of natives to form startups with migrants. Specifically, motivated by the fact that 31% of startups are co-founded by entrepreneurs who attended the same university-degree program, we use as an instrument the native share in the degree program at the university the native founder attended, in the year he attended. Intuitively, the proportion of native students in the degree program the native founder attended should impact the likelihood that individual collaborates with migrants when forming a startup. Our first-stage regression results confirm this with university-by-degree fixed effects. The exclusion restriction is then that residual variation in within university-degree native shares is uncorrelated with other drivers of startup success.

Our two-stage least squares (2SLS) estimates generally confirm the conclusions of the OLS analysis and, in fact, are consistently larger.[1] Relative to native-only startups, native-migrant startups are approximately 44% larger in terms of employment size three years following inception. Native-migrant startups are 35 percentage points more likely to receive funding within three years and raise substantially more funding than native-only startups. While the OLS results show an impact of native-migrant teams on acquisition and IPO, we are however not able to detect such effects in the 2SLS regressions, likely due to these regressions being quite under-powered. We then repeat a similar instrumental variable analysis within a sample of startups with at least one migrant co-founder and confirm that the superior performance of native-migrant startups, compared to migrant-only startups, is not driven by the selection of higher-quality migrants into co-founding with natives.

Our two-stage least squares (2SLS) results also provide supporting evidence for the underlying mechanisms. Relative to native-only tearms, native-migrant teams are more likely to hire migrant workers, hire higher-quality migrant workers, are more likely to access foreign VC capital, and are more likely to source capital from top VCs, measured by number of deals and number of successful exits. The results also indicate that native-migrant teams are more likely to file a foreign patent than native-only teams, although the result is not statistically significant, again likely due to this regression being under-powered. Turning now to the comparison between native-migrant teams and migrant-only teams, native-migrant teams hire more native workers, hire higher-quality native

[1] In Section 5.4, we show that that this difference in magnitudes can largely be accounted for by the outperformance of founders who attend the same university-degree program and potential downward bias in the OLS estimates due to migrant outside options and project selection.

workers, are more likely to source capital from top domestic VCs, and are more likely to be granted a US patent. Together, these results provide additional causal evidence that the outperformance of native-migrant startups can be attributed to superior labor market access, capital market access, and product market access.

To address remaining endogeneity concerns that the share of native students could be correlated with unobserved location factors influencing the future performance of native-migrant startups, we perform a variety of robustness tests. First, we show that local economic conditions, such as GDP growth, VC financing growth, job creation growth, and new firm entry growth, are uncorrelated with the native share. Second, we conduct a placebo test showing that the native share does not predict the performance of native-only or migrant-only firms. Finally, we estimate the results using an even more stringent shift-share design. Specifically, to construct our instrument we interact the average share of students in a given university-degree program from 1995-1999, a five-year window preceding our sample period, with national fluctuations in the number of US natives pursuing a particular degree across all US universities. This more stringent specification generates results that are both qualitatively and quantitatively similar to the baseline 2SLS results.

The paper proceeds as follows. Section 1.1 relates our work to the prior literature. Section 2 describes our data and sample construction. Section 3 presents our baseline OLS results, while Section 4 presents results on the underlying mechanism and associated heterogeneity tests. Section 5 details our IV strategy and presents our 2SLS results. Section 6 concludes.

1.1 Literature Review

Our paper contributes to several strands of literature. First, an emerging body of work examines the disproportionate role of immigrants in entrepreneurship and startups. Kerr (2013) and Kerr and Kerr (2016) highlight the growing impact of immigrant-founded startups on the US economy, while Azoulay et al. (2022) use US administrative data to show that immigrant entrepreneurs are pivotal in job creation, particularly through fast-growing startups. Fairlie and Lofstrom (2015) and Chodavadia et al. (2024) provide comprehensive reviews of immigrants' outsized contributions to business creation and innovation.

A related literature explores immigrant contributions to US innovation. Hunt and Gauthier-Loiselle (2010) and Hunt (2011) find that immigrants, especially those on student or temporary visas, patent at twice the rate of US natives. Bernstein et al. (2022) report that immigrant innovators are 40% more productive in patenting than their US-born counterparts, a figure that rises to 50% when adjusting for a patent quality measure based on Kogan et al. (2017). They also show that immigrant inventors rely more on foreign technologies and are twice as likely to collaborate with foreign inventors compared to natives.[2] Our contribution to this literature is twofold: we demonstrate that synergies between native and immigrant co-founders lead startups with mixed teams to outperform those founded solely by either group. Furthermore, through our heterogeneity tests and IV strategy, we shed light on the specific channels through which these native-immigrant synergies drive enhanced startup outcomes.

Second, our paper contributes to the literature on the importance of ethnic ties and social networks in transmitting ideas and accessing finance and labor for startups. Saxenian (2002) and Kerr (2008) highlight the role of ethnic networks in cross-border technology diffusion. Hegde and Tumlinson (2014), Balachandran and Hernandez (2021), and Eghbali, Wallskog, and Yi (2024) study the role direct and indirect ethnic ties play in the deployment of capital by venture capital funds (VCs). We contribute to this literature by showing that having both a native and immigrant co-founder can significantly expand the startup's options for funding, hiring, and market access, ultimately leading to better startup outcomes.

Finally, we contribute to the empirical literature on team diversity. Freeman and Huang (2015), Gompers, Mukharlyamov, and Xuan (2016), and Lu, Naik, and Teo (2024) find a positive correlation between team diversity and productivity in academic co-authorship, VC funds, and hedge funds. While studies on endogenous team formation typically show a positive link between diversity and performance, research on randomly assigned teams often finds a negative correlation between diversity and outcomes (Hjort (2014), Lyons (2017), Calder-Wang, Gompers, and Huang (2021)). Consistent with studies on endogenous teams, we find that startups with both migrant and native founders outperform migrant-only or native-only firms. Our IV strategy, which leverages variations in the share of natives across different university programs and over time, confirms that these positive synergies are not driven solely by endogenous selection. Instead, in the context of immigrant-native entrepreneurial collaboration, expanded access to high quality labor and financing pools, as well as increased access to product markets, appears to drive the improved outcomes.

[2] See also Kerr et al. (2016) and Beerli et al. (2021) on the role of global talent in driving firm-level innovation.

2 Data and Sample Construction

This section discusses our data sources, the process we use to construct our sample, and presents summary statistics at both the entrepreneur and firm levels.

2.1 Data

Our research primarily relies on two databases: Revelio Lab and Crunchabse. We rely on the Crunchbase database to collect information on startups. The data presents comprehensive firm-level information such as the company website, company LinkedIn URL, founding date, funding, investor, acquisition, IPO, geography, and industry. One of the advantages of Crunchbase over other commercial databases is its broad coverage due to crowdsourcing and data coverage from TechCrunch. As a result, the Crunchbase sample includes startups that are not VC financed, unlike other databases such as VentureXpert or Pitchbook that focuses on VC-backed startups. As other recent papers have laid out in detail (e.g. Koning, Hasan, and Chatterji (2022), Lee and Kim (2023), Gofman and Jin (2024)), Crunchbase is well-positioned to capture startup activities.[3]

We use Revelio Labs to collect individual information on startup founders and employees. Revelio Lab is a workforce intelligence company established in 2018 that gathers information from LinkedIn profiles (i.e., online resumes) of more than 850 million individuals in over 200 countries. A typical LinkedIn profile includes a user's employment history, educational background, and skillset. For each employment record listed by a user, the start and end dates of the job tenure are provided, along with the corresponding employer's name, job title, and job location. In addition, Revelio Lab also provides each individual's unique identifier, predicted gender, predicted ethnicity, employer unique identifier, and employer LinkedIn profile URL.

Individuals with a college education and those in white-collar jobs are more likely to have a LinkedIn profile compared to those without higher education or in blue-collar positions. Tambe (2014) shows that a large portion of the white-collar workforce uses LinkedIn, including over 80% of the total US IT workforce. Moreover, comparing the number of college-educated LinkedIn users with data from the ACS suggests that LinkedIn covers more than 60% of the college-educated labor force in the U.S. (Khanna and Morales (2025), Amanzadeh, Kermani, and McQuade (2024)).

[3] In section IA.1 in the Internet Appendix, we provide additional information about Crunchbase coverage. Moreover, to ensure our findings are not influenced by firm coverage in Crunchbase, in section IA.3 in the Internet Appendix, we replicate our labor-related findings using only the LinkedIn database.

Therefore, we consider LinkedIn a more representative platform for college-educated individuals and white-collar professions and well-positioned to capture entrepreneurs and startup employees in the US (e.g. Lee and Kim (2023), Jeffers (2024) , Gofman and Jin (2024)).

To identify migrant entrepreneurs in the LinkedIn dataset, we first identify entrepreneurs by selecting individuals with job titles reported on the LinkedIn profiles that contain the key words: "founder", "co-founder", or "cofounder". Next, to construct a measure of migrant status, we follow Gupta (2023) and Amanzadeh, Kermani, and McQuade (2024) to define home country as the initial country that appears in an individual's LinkedIn profile, either in educational pursuits or job positions. Then if an entrepreneur with a non-US home country establishes a company in the US, he or she would be identified as a migrant entrepreneur in our sample. Our measure of migrants could miss those individuals who are migrants but with LinkedIn profiles listing the initial country as the US. Thus, the number of migrant entrepreneurs in our sample represents a lower bound of the actual number of migrant entrepreneurs.

2.2 Sample construction

To combine individual-level information from Revelio Labs with firm-level information from Crunchbase, we merge these two datasets according to the following process. First, we remove firms founded before 2000, investment firms, and non-profit organizations from the Cruchbase dataset. Second, we remove firms without any founder profile listed in LinkedIn from the Revelio Labs data. We then merge the remaining firms in LinkedIn with those in Crunchbase using the company LinkedIn profile URLs, which are available in both datasets.

Specifically, in addition to individual profiles, many US firms maintain their own LinkedIn profiles, which they use to post company updates, job vacancies, and facilitate employee networking. Approximately 70% of US-based firms in the Revelio Labs database have profiles, and about 85% of US-based firms in Crunchbase provide LinkedIn profile URLs. Unlike firm names, LinkedIn profile URLs are unique identifiers and follow a consistent format across different databases. Therefore, using LinkedIn profile URLs allows us to accurately identify firms present in both the Revelio Labs and Crunchbase datasets.

We begin with 434,130 firms from Crunchbase that have LinkedIn URLs and were founded between 2000 and 2022. After merging with LinkedIn data, we retain 312,574 firms, reflecting a 72% match rate. We then restrict the sample to the US-based firms, defined as those either explicitly labeled as the US firms in Crunchbase or with at least one founder whose job location is listed in the US. This yields 130,010 US-based firms. In addition, to remove potential fake LinkedIn accounts, we compare the founder's reported start year on LinkedIn with the firm's establishment year from Crunchbase. If a founder's reported start year is more than two years later than the establishment year, we exclude that founder. We also exclude firms that have not had any employees (excluding founders) within three years of their inception to avoid including shell firms. Our final sample consists of 134,761 distinct entrepreneurs who founded 90,834 startups in the US between 2000 and 2022.

2.3 Migrant Entrepreneurs in the US from 2000 to 2022

Panel A of Figure 1 illustrates the shares of migrant entrepreneurs and different types of migrant entrepreneurs relative to the total number of entrepreneurs in the US over our sample period of 2000-2022. The share of migrant entrepreneurs has been steadily increasing from about 12% in 2000 to 27% in 2022. The shares of migrant entrepreneurs at different points in time are largely consistent with those reported in Chodavadia et al. (2024). In addition, Panel A of Figure 1 classifies migrant entrepreneurs into four distinct categories: (1) migrant entrepreneurs who establish startups without co-founding with others (*Single_Founder*), (2) migrant entrepreneurs who co-found startups with native entrepreneurs (*Migrant_Native*), (3) migrant co-founders with the same country of origin (*Same_Origin*), and (4) migrant co-founders with different country of origins (*Mixed_Origin*). In Panel A of Figure IA1 in the Internet Appendix, we also show the relative share of each type within migrant entrepreneurs. Unlike the shares of migrant entrepreneurs, the relative shares of each type within migrant entrepreneurs have been relatively stable over the past decades.

Panel B of Figure 1 displays the top ten home countries of migrant entrepreneurs based on the number of startups they have founded in the US from 2000 to 2022. India leads with 4,654 startups established by Indian founders, followed by the UK with 3,032 startups founded by UK entrepreneurs and Canada with 2,485 startups founded by Canadian entrepreneurs. Among the top three countries, migrant entrepreneurs from the UK and Canada are more likely to co-found a startup with native entrepreneurs. Specifically, about half of startups founded by the UK and Canadian entrepreneurs are co-founded with the US entrepreneurs. In contrast, only one third of startups founded by Indian entrepreneurs are co-founded with native entrepreneurs. Panel B of Figure IA1 in the Internet Appendix illustrates the share of migrant entrepreneurs by the top ten countries over time. Consistent with the overall trend shown in Figure 1, the shares of migrant entrepreneurs from all ten countries demonstrate an increasing trend.

Panel C of Figure 1 displays the top ten industries based on the proportion of startups founded by migrant entrepreneurs relative to the total number of startups in each industry. Industry classification is derived from business categories assigned by Crunchbase. For firms with multiple business categories, we use Sentence-BERT (SBERT) to select the category most closely aligned with the firm's business description.[4] *Artificial intelligence*, *blockchain and cryptocurrency*, and *data and analytics* are the leading sectors, with 36%, 30%, and 28% of their startups founded by migrant entrepreneurs, respectively. In Figure IA2 in the Internet Appendix, we rank the top ten industries by the total number of startups founded by migrant. The top three industries are *sales and marketing* (1,886 startups), *commerce and shopping* (1,857 startups), and *software* (1,831 startups).

2.4 Summary statistics

In this section, we present summary statistics for the sample used in our analysis. We restrict the sample to startups that (1) were established no later than 2017 and (2) have at least two co-founders. The sample stops in 2017 to allow for a minimum of five years to assess two key outcome variables: the probability of acquisition within five years of inception and the likelihood of an IPO within ten years of inception. We further exclude single-founder startups to ensure a fair comparison between migrant-native co-founded startups versus those founded solely by natives or migrants because more promising ventures may be more likely to attract additional co-founders.[5]

Table 1 compares the characteristics of native and migrant entrepreneurs. Generally, migrant entrepreneurs exhibit higher educational attainment compared to their native counterparts. This is evident from a greater percentage of migrant entrepreneurs holding advanced degrees, such as master's, MBA, or PhD degrees, and from the higher proportion of those degrees being earned from top 50 and top 100 universities. Furthermore, in terms of previous work experience before

[4]Business description in the Crunchbase is typically one-sentence long, and business category is typically two-words long. SBERT could directly generate embeddings for the entire sentence, capturing the overall meaning and context of the sentence. Therefore, SBERT is more efficient to measure semantic similarity between the business description and category than other language models of token-based embeddings. For more information on SBERT, please see https://www.sbert.net

[5]Table IA1 and IA2 in the Internet Appendix present individual-level and startup-level summary statistics without excluding single founders.

starting new ventures, migrant entrepreneurs are more likely to have held managerial, engineering, or scientific positions. In contrast, they are less likely to have experience in finance, marketing, sales, or operations.[6]

Panel A of Table 2 presents summary statistics at the firm level. The sample includes 22,967 startups founded between 2000 and 2017 that have at least two co-founders. In this sample, 33% of startups have least one migrant founder, and 22% of startups have both migrant and native founders, indicating that 11% are founded solely by migrant founders. About 30% of the average startup's workforce consists of migrant employees. On average, startups hire 26 employees in three years since the firm inception year. Within the first three years of the inception year, 36% of startups have received external financing with an average funding amount of 44 million US dollars and 18% have received financing from VCs based outside of the US. About 6% of startups are acquired within five years of establishment, and approximately 1% of firms go public within ten years of establishment.

Panel B of Table 2 presents a preliminary univariate analysis comparing migrant-native startups to both native-only and migrant-only startups. Migrant-native startups exhibit superior performance along several dimensions, including larger employment size, a higher likelihood of securing external financing, larger funding rounds, and a greater chance of being acquired or going public.

Table IA3 in the Internet Appendix presents a comparison of native and migrant employees who joined startups within the first five years of the firms' founding. Migrant employees are less likely than their native counterparts to hold undergraduate degrees as their highest level of education, but are more likely to possess graduate-level degrees, including master's, MBA, or PhD degrees. Among native employees, 33% hold a bachelor's degree as their highest degree, and 18% have earned a graduate degree. In contrast, 20% of migrant employees hold only a bachelor's degree, while 21% possess graduate degrees. In terms of functional roles, migrant employees are disproportionately represented in engineering positions and underrepresented in business-oriented roles such as marketing and sales. Specifically, 39% of migrant employees work in engineering, compared to 19% of native employees. Conversely, 29% of migrant employees are employed in marketing or sales roles, whereas the corresponding figure for native employees is 44%. These differences underscore distinct patterns in educational background and occupational specialization between native and migrant startup employees.

[6] University ranking and job category data are provided by Revelio Lab.

3 Migrant Entrepreneurs and Startup Performance

Next, we present baseline OLS results that examine the relative performance of startups founded by migrant entrepreneurs and native-migrant teams. Specifically, we investigate whether the performance of startups differs based on whether they were founded by migrant or native entrepreneurs and, additionally, whether performance varies between startups founded solely by migrant entrepreneurs and those co-founded by native-migrant teams.

3.1 Empirical design

Startup performance is measured by the logarithm of employment size in three years after inception ($ln(Emp_{t+3})$), the likelihood of receiving funding within three years of inception ($Funded_{[t,t+3]}$), the logarithm of total amount of funding raised within three years plus one ($ln(Raised_{[t,t+3]})+1$), the probability of acquisition within five years ($Acq_{[t,t+5]}$), and the probability of going public within ten years ($IPO_{[t,t+10]}$). We start with the following OLS specification:

$$Performance_{i,[t,t+\tau]} = \beta_1 Migrant_{i,t} + \beta_2 Migrant\_Native_{i,t} + \boldsymbol{\Gamma'X}_{i,t} + \alpha_{j,t} + \varepsilon_{i,t}, \qquad (1)$$

where $Migrant_{i,t}$ is an indicator that is equal to one if startup i founded in year t has at least one migrant founder, $Migrant\_Native_{i,t}$ is an indicator that is equal to one if startup i founded in year t has both migrant and native founders, $\alpha_{j,t}$ are industry×inception year fixed effects, and $\boldsymbol{X}_{i,t}$ represents a set of control variables. This set includes an indicator that is equal to one if at least one of the founders holds a bachelor's degree as the highest degree (*Bachelor*), an indicator that is equal to one if at least one of the founders holds a master's, MBA, or PhD degree as the highest degree (*Graduate*), an indicator that is equal to one if at least one of the founders has prior founder experience (*Seiral_Entrepreneur*), the maximum number of years of work experience prior to founding the current startup i among all the founders (*Experience*), and an indicator that is equal to one if at least one of the founders previously held a managerial positions (*Manager*). It further includes the number of founders (*Number_Founders*), an indicator that is equal to one if at least one of the founders obtained a degree from top 10 universities (*Top10_University*), an indicator that is equal to one if at least one of the founders obtained a degree from universities ranked between top 10 and top 50 (*Top50_University*), and an indicator that is equal to one if at least one of the founders obtained a degree from universities ranked between top 50 and top 100 (*Top100_University*). Finally, it includes an indicator that is equal to one if all of the co-founders in a startup have previous working experience in engineer- or science-related positions (*Tech_Tech*), and an indicator that is equal to one if at least one co-founder has prior work experience in marketing, operations, or finance, and at least one co-founder has prior work experience in engineering or science (*Tech_Business*). The robust standard errors are clustered at the industry$\times$year level.

The estimates of β_1 and β_2 examine the impact of migrant entrepreneurs on startup performance. Including β_1 alone in equation (1) measures the effect of migrant founders on startup performance relative to startups founded solely by native founders. By adding *Migrant_Native* to equation (1), which is equal to one if a startup has both migrant and native founders, β_1 then captures performance difference between migrant-only startups and native-only startups, while β_2 represents the performance difference between migrant-native-co-founded startups and migrant-only startups.

3.2 Baseline results

Table 3 presents OLS estimates based on equation (1). The sample contains startups established between 2000 and 2017 to provide at least a five-year window to assess the acquisition and IPO outcome by the end of our analysis period in 2022. To ensure a fair comparison of performance between migrant-native-co-founded startups and native-only startups, we exclude startups with single founders, as the former inherently have at least two co-founders. This approach helps control for potential biases, as promising projects may attract more founders. By focusing on startups with multiple founders, we aim to more accurately assess the impact of having both migrant and native founders on performance, rather than reflecting differences in project quality.

Columns (1) and (2) show the effects of migrant founders on employment size three years after the firm's inception. In column (1), the coefficient on *Migrant* is 0.2, statistically significant at 1% level. Since the dependent variable is log-transformed, the employment size of startups with at least one migrant co-founder is roughly 20% larger than startups founded solely by native founders. In column (2), we add *Migrant_Native* to examine whether startups founded by both migrants and natives perform better than those founded solely by migrant founders. The coefficient on *Migrant_Native* is 0.079, statistically significant at 1% level, and the coefficient on *Migrant* reduces from 0.2 in column (1) to 0.15 and remains statistically significant at 1% level. These results suggest that migrant-native-co-founded startups' employment size three years after establishment is about 8% larger than migrant-only startups, and the employment size of migrant-only startups is about 15% larger than that of native-only startups.

In terms of funding outcomes, columns (3) to (6) indicate that migrant-founded startups have a higher likelihood of being funded and raise significantly more capital within three years of establishment. Migrant-native co-founded startups also raise substantially more capital than startups solely founded by migrants. Specifically, in column (3), the coefficient on *Migrant* is 0.052 and statistically significant at 1% level. As for the economic significance, a coefficient of 0.052 represents a 17% increase relative to the sample average of the dependent variable, $Funded_{[t,t+3]}$. In column (4), we find that the presence of both migrant and native founders does not significantly affect the likelihood of receiving funding compared to migrant-only startups as the coefficient on *Migrant_Native* is statistically insignificant. In column (5), the coefficient on *Migrant* is 0.138, statistically significant at 1% level, while column (6) reveals that the inclusion of *Migrant_Native* renders the effect of *Migrant* insignificant and highlights that the positive funding effect is primarily driven by migrant-native-co-founded startups, with *Migrant_Native* having a coefficient of 0.19 significant at the 1% level.

We examine the acquisition outcome in columns (7) and (8). In column (7), we do not find a statistically significant impact of migrant entrepreneurs on the likelihood of acquisition within five years of establishment. Column (8) shows that the chance of getting acquired for migrant-only startups is 2.5% lower than native-only startups, while migrant-native-co-founded startups have a 2.8% higher acquisition likelihood compared to migrant-only startups, which represents a 47% increase relative to the sample average of $Acq_{[t,t+5]}$. These results also suggest that migrant-native startups have a 0.3% (= 2.8% − 2.5%) higher chance to be acquired within five years of inception than native-only startups.[7] This represents a 5% increase relative to the sample average of $Acq_{[t,t+5]}$.

Finally, columns (9) and (10) show the impact of migrant entrepreneurs on the likelihood of going public within ten years of inception. Column (9) indicates a significant coefficient of 0.004 for *Migrant* at the 5% level, reflecting a 40% increase in IPO likelihood relative to the sample average. Column (10) shows that the positive effect on IPO probability is solely attributed to migrant-native-co-founded startups, as the coefficient for *Migrant* becomes insignificant, while *Migrant_Native* has a coefficient of 0.005 with a 10% significance level.

Overall, the baseline results in Table 3 reveal that migrant-founded startups have significantly

[7] The 0.3% higher chance is statistically significant at 10% level.

larger employment sizes compared to native-founded ones, with migrant-native-co-founded startups exhibiting the largest employment growth. In terms of funding likelihood, migrant-founded startups are more likely to receive funding, though the presence of both migrant and native founders does not show a significantly higher likelihood. For the funding amount, migrant-only startups do not differ from native-only startups, while migrant-native-co-founded startups receive significantly more funding than native-only startups. Acquisition outcomes indicate that migrant-native-co-founded startups are more likely to be acquired than native-only startups, while migrant-only startups in fact have a lower likelihood than native-only startups. Finally, while migrant-only startups show no increase in IPO likelihood relative to native-only startups, there is a substantial increase (40% relative to the sample mean) in the chance of going public within ten years of establishment for startups co-founded by both migrants and natives.

3.2.1 Robustness checks of baseline results

In this section, we examine whether our baseline results are robust to alternative sample selection and empirical specifications. Panel A of Table IA4 in the Internet Appendix presents OLS estimates at the startup-founder level instead of the startup level used in our baseline results. We also restrict the sample to include entrepreneurs with a US college degree such that we can also control for the university and degree fixed effects. Without the university and the degree fixed effects, the findings in Panel A are qualitatively and quantitatively similar to baseline results. Once we control for these two sets of fixed effects, the performance of migrant-only startups, relative to native-only startups, become similar, while the migrant-native co-founded startups still outperform both migrant-only and native-only startups.

Panel B of Table IA4 in the Internet Appendix presents OLS estimates based on startups with both single and multiple founders. Moreover, we add the number of founders as additional fixed effects to equation (1). The results are largely consistent with the baseline results presented in Table 3. In Panel C of Table IA4, we restrict the sample to startups that have already received external funding within the three years of their inception. We then conduct our analysis conditional on firms receiving financing. The sample contains 7,192 startups with at least two co-founders. The OLS estimates for employment, the amount of funding, the probability of getting acquired, and the chance of going public are both qualitatively and quantitatively similar to the baseline results presented in Table 3. In Panel D, we add State$\times$Est. Year fixed effects to our baseline specification and the results are almost identical to our baseline results reported in Table 3.

Panel E of Table IA4 in the Internet Appendix examines the impact of migrant founders on the amount of funding received within the first three years of establishment. Given that 64% of startups do not receive any external financing in our sample used for baseline results in Table 3, resulting in a funding amount of zero, we take the logarithm of funding amount plus one. However, to deal with potential estimation bias arising from log-linear regressions, we follow Chen and Roth (2024) and use Poisson regressions without applying a log transformation to the funding amount. The Poisson estimates reported in Panel C of Table IA4 are consistent with the baseline results obtained using OLS estimation.

3.2.2 Startup Failure

Beyond traditional measures of startup success, this section examines whether migrant-only and migrant-native startups are less likely to fail compared to native-only startups. We define failure based on employment size (excluding founders/co-founders) five years after inception, using three indicators: (1) whether the firm has no employees in $t+5$, (2) whether it has no more than three employees in $t+5$, and (3) whether it has no more than five employees in $t+5$. We estimate the baseline specification (equation (1)) using these failure measures as dependent variables, with results presented in Table IA5 in the Internet Appendix. Across all three failure definitions, the coefficients on *Migrant* are negative, ranging from -0.06 to -0.03, and statistically significant at the 1% level, indicating that migrant-only startups are 3% to 6% less likely to fail than native-only startups. In contrast, the coefficients on *Migrant_Native* are insignificant across all specifications, suggesting no significant difference in failure rates between migrant-native and migrant-only startups.

3.3 False positives in identifying native-migrant startups

As discussed earlier, our identification of immigrant status is based on the initial country listed in an individual's LinkedIn profile. Since many initial countries correspond to the locations of universities, our measure of migrants may overlook individuals who, despite being migrants, obtained their bachelor's or graduate degrees in the US.

This measurement error could lead to two issues. First, for individuals who list US graduate degrees but do not report undergraduate institutions, there is a considerable chance that the undergraduate institutions are outside the US. To address this issue, we restrict the sample to startups with all of the co-founders who list their undergraduate institutions. The firm-level results are reported in Panel A of Table IA6 in the Internet Appendix and are largely consistent with those without this restriction, that is, the baseline results shown in Table 3.

The second issue is that some migrants may come to the United States for their undergraduate education and this may be the first entry on their LinkedIn profile. On the one hand, this implies that their formative educational years are spent in the United States, and they may thus be more similar to US natives than migrants who come later. Still, to address the extent to which our results may be driven by such early migrants, we exclude native-migrant startups in which migrant founders come from countries with a disproportionately high share of immigrants who earned the US bachelor's degrees. This step helps remove native-migrant startups that should have been classified as migrant-only.[8]

We use the international student data from the Institute of International Education and the US immigration data from Migration Policy Institute to calculate the share of immigrants with US bachelor degrees for each non-US country.[9] We then exclude native-migrant startups with founders from the top-10 countries in terms of the share of immigrants with US bachelor's degrees. These countries are: Saudi Arabia, Kuwait, Malaysia, Singapore, Sweden, Indonesia, Nepal, Norway, China, and the Bahamas, with Saudi Arabia having the highest share at 33%, and the Bahamas the lowest at 4.5%. We repeat the baseline specification without those native-migrant startups at both the firm and founder level and report the results in Panel B of Table IA6 in the Internet Appendix. The estimates are almost unchanged when those native-migrant startups are excluded, which suggests that our baseline results are unlikely to be subject to this measurement error.

4 Mechanisms

In this section, we explore a set of potential mechanisms that might explain why migrant-native co-founded startups outperform migrant-only and native-only startups. Specifically, we consider the following three explanations:

1. **Dual access to immigrant and native labor pools**: Migrant-native co-founded startups benefit from the combined networks of both migrant and native founders. Migrant founders

[8] In our sample, about two-thirds of migrant-only startups have co-founders from the same country.

[9] For more information, please see https://opendoorsdata.org/data/international-students/enrollment-trends/ and https://www.migrationpolicy.org/programs/migration-data-hub

can tap into immigrant labor networks, which may offer specialized skills or cost advantages, while native founders provide connections to native talent. The ability to draw from both labor markets may explain why migrant-native startups outperform their migrant-only and native-only counterparts, as they can optimize hiring strategies in a broader and more diverse talent pool.

2. **Dual access to foreign and domestic investors**: Migrant founders often maintain connections with investors in their home countries, providing access to international capital sources that native founders may lack (Eghbali, Wallskog, and Yi 2024). At the same time, native founders have stronger connections with domestic investors who may be more familiar with the domestic market and regulatory environment. This dual access enables migrant-native co-founded startups to attract both domestic and international investment. As a result, this advantage may contribute to their superior performance compared to migrant-only and native-only startups.

3. **Dual access to overseas and domestic product markets**: Lastly, migrant-native co-founded startups can leverage the global networks and market knowledge of migrant founders while capitalizing on the domestic expertise and regulatory understanding of native founders. This combination enhances their ability to navigate both foreign and domestic markets effectively. The dual-market strategy enables these startups to pursue international opportunities while maintaining a strong foothold in the US market. This synergy may explain why migrant-native startups outperform their migrant-only and native-only counterparts, as they are better equipped to scale operations and capture market share both locally and abroad.

4.1 Combining the strengths of both migrant and native founders

In this section, we provide evidence that migrant-native startups outperform both migrant-only and native-only startups by combining the strengths of both migrant and native labor pools, foreign and domestic VC markets, and international and domestic product markets.

Figure 2 breaks down the composition of employees and venture capital (VC) investors by country. Panel A shows the average employee composition across startups in our sample and highlights that migrant employees make up 18% of the workforce in native-only startups. In contrast, startups with migrant founders demonstrate significantly higher proportions of migrant employees:

74% in migrant-only startups and 47% in migrant-native startups. Notably, the majority of migrant employees in these startups come from the same country as the migrant founders. Specifically, 66% of migrant employees in migrant-only startups share the same home country as the founders and 45% in migrant-native startups.

Panel B presents the average VC composition across startups that receive VC financing three years within the inception. In native-only startups, foreign VCs represent just 8% of all investors. Startups with migrant founders exhibit a much larger share of foreign VCs: 43% in migrant-only startups and 23% in migrant-native startups. Similarly to the labor composition, the higher share of foreign VCs is predominantly driven by investors from the founders' home countries. Among foreign VCs, 65% in migrant-only startups and 43% in migrant-native startups are based in the same country as the migrant founders.

These summary statistics suggest that migrant founders contribute to higher shares of employees and VCs from their home countries, with migrant-only startups exhibiting the highest concentration of such connections. Migrant-native startups, however, achieve a more balanced mix, combining domestic and international labor and funding sources.

4.1.1 Leveraging strengths in migrant and native labor pool

Table 4 investigates whether startups with migrant founders hire more migrant employees, whether migrant founders are better at hiring high-quality migrant workers, and whether native founders are more effective at hiring high-quality native workers. Employee quality is measured by the share of workers hired within the first five years of the firm's inception who are subsequently promoted within three years of joining. Promotions are measured according to Revelio Labs firm seniority rankings. See Appendix Table A1 for details. To address potential concerns about internal promotions, such as favoritism (e.g., migrant founders promoting migrant workers disproportionately), we analyze both internal promotions within the firm and promotions after employees transition to other firms (external promotions). External promotions are more likely to be merit-based and less influenced by favoritism, offering a more objective measure of employee quality (Gupta, Nishesh, and Simintzi (2024)).

In column (1), the results show that migrant-only startups employ a significantly higher share of migrant workers compared to native-only startups, with the coefficient on *Migrant* being 0.548 (significant at the 1% level). This indicates that migrant founders tend to hire disproportionately more migrant employees relative to native-only firms. In contrast, firms co-founded by both migrant and native entrepreneurs exhibit a negative coefficient (-0.277, significant at the 1% level) on *Migrant_Native*, suggesting they employ a smaller share of migrant workers compared to migrant-only startups. However, relative to native-only startups, migrant-native startups still hire 27.1% more migrant employees ($= 100 \times (0.548 - 0.277)$), representing a 91% increase compared to the sample average.

In columns (2) to (4), we present OLS regression estimates using the share of external promotions as a proxy for labor quality. Column (2) examines the effects on the share of all external promotions. The coefficient on *Migrant_Native* is positive and statistically significant at 1% level, while the coefficient on *Migrant* is insignificant. These results indicate that migrant-native startups hire more high-quality workers than native-only or migrant-only startups. These results align with our baseline findings, where migrant-native startups exhibit the best overall performance. In columns (3) and (4), we further disaggregate the share of external promotions into migrant and native external promotions, respectively. The share of migrant (native) promotions is calculated by dividing the number of migrant (native) promotions by the number of migrant (native) employees. In columns (3) and (4), the coefficients on *Migrant* show that migrant-only startups are positively associated with the share of high-quality migrant workers (0.028, significant at the 1% level), but negatively associated with the share of high-quality native workers (-0.026, significant at the 1% level). These results suggest that migrant founders are more adept at hiring high-quality migrant workers but face challenges in hiring high-quality native workers.

In column (3), the coefficient on *Migrant_Native* is insignificant, indicating that migrant-native startups do not have any disadvantage over migrant-only startups in terms of hiring high-quality migrant workers. In column (4), the coefficient on *Migrant_Native* is 0.025 and statistically significant at the 1% level. This magnitude is comparable to the negative coefficient on *Migrant* (-0.026), suggesting that in migrant-native startups, native co-founders complement migrant co-founders in hiring high-quality native workers, thereby offsetting the challenges faced by migrant-only startups in this regard.

In columns (5) to (7), we present OLS regression estimates using internal promotions as the proxy for employee quality. Despite the issues related to this measure discussed above, the results in columns (5) to (7) are both qualitatively and quantitatively similar to those in columns (2) to (4), reinforcing the finding that migrant founders are more effective at hiring migrant employees, native founders are better at hiring native employees, and migrant-native startups leverage the strengths of both groups.[10]

4.1.2 Combining strengths in foreign and domestic VC networks

Table 5 explores whether startups with migrant founders are more likely to secure funding from foreign VCs and attract top-tier foreign VCs, and whether native founders are more successful in attracting top domestic VCs. Top VCs are defined as those ranked in the top ten percentiles based on the number of past deals or successful exits.

In column (1), we first examine whether startups with migrant founders are more likely to receive funding from VCs based outside the US. The results show that migrant-only startups are 11.3% more likely to receive funding from foreign VCs compared to native-only startups. The coefficient on *Migrant* is 0.113, significant at the 1% level, which corresponds to a 68% increase relative to the sample average. However, for migrant-native co-founded startups, the coefficient is negative (-0.036, significant at the 1% level), indicating a lower likelihood of attracting foreign VCs compared to migrant-only startups. Despite this, migrant-native startups are still 7.6% ($= 100 \times (0.113 - 0.037)$) more likely to secure foreign VC funding than native-only startups, representing a 48% increase relative to the sample average.

In columns (2) to (4), we report Poisson regression estimates for the number of top VCs defined by the number of past deals. Column (2) examines the total number of top VCs that invest in startups during the first three years of their inception. The coefficient on *Migrant_Native* is positive and statistically significant at the 1% level, while the coefficient on *Migrant* is not significant. These results suggest that migrant-native startups attract more top VCs than migrant-only startups, while migrant-only startups are equally attractive to top VCs as native-only startups.

In columns (3) and (4), we disaggregate the total number of top VCs into foreign and domestic VCs. Migrant-only startups are positively associated with the number of top foreign VCs (coefficient of 1.457, significant at the 1% level) in column (3), but negatively associated with the number of domestic VCs (coefficient of -0.451, significant at the 1% level) in column (4). These results indicate that migrant-only startups are more favored by foreign VCs, but less favored by domestic VCs. Meanwhile, the coefficient on *Migrant_Native* is -0.418 and statistically significant

[10] In Panel A of Table IA7 in the Internet Appendix, we present individual-level analyses, and in Panel B of Table IA7 in the Internet Appendix, we present firm-level analyses for migrant employees from ten specific countries. The results from both analyses confirm that more promotions of migrant workers are mainly concentrated in workers from the same country as migrant founders' home country.

at the 1% level, suggesting that migrant-native startups attract fewer top foreign VCs compared to migrant-only startups. Nevertheless, relative to native-only startups, migrant-native startups still attract 130% more foreign VCs ($= 100 \times (e^{1.457-0.418} - 1)$). In column (4), the coefficient on *Migrant_Native* is 0.453 and statistically significant at the 1% level, which is comparable to the magnitude of the negative coefficient on *Migrant* (-0.451), suggesting that native co-founders in migrant-native startups complement migrant co-founders in attracting top domestic VCs. [11]

In columns (5) to (7), we report Poisson regression estimates using the number of top VCs defined by the number of successful exits. The results are broadly consistent with those in columns (2) to (4), reinforcing the notion that migrant founders are more adept at attracting top foreign VCs, native founders are preferred by top domestic VCs, and migrant-native co-founded startups are able to combine the strengths of both groups in attracting top VCs.

4.1.3 Combining strengths in foreign and domestic product market

Finally, we provide evidence on whether migrant founders have an inherent advantage in accessing foreign markets, native founders have a competitive advantage in understanding domestic markets, and migrant-native startups could combine the strengths of both groups.

Since we cannot directly observe market access, we use patents as a proxy for market entry. The rationale behind this proxy is twofold. First, firms typically seek patent protection in countries where they intend to commercialize their innovations or anticipate competitive threats, as securing intellectual property rights can protect market share and prevent imitation. Second, the costs associated with patent filings are substantial, meaning that firms are unlikely to pursue patents unless they expect tangible economic returns from certain markets. Especially for the international market expansion, the presence of patents can be viewed as a strong indication that the firm is actively engaging in international activities, making it a useful proxy for market entry into overseas territories.

Table 6 investigates startups' overall patenting activities as well as the patenting activities in non-US countries and the US separately. In columns (1) to (3), we report Poisson regression estimates for the number of granted patents filed by startups. The coefficient on *Migrant* in column (1) is negative and statistically significant at the 1% level, indicating that migrant-only startups have 41% (=$100 \times (e^{-0.529} - 1)$) fewer granted patents overall than native-only startups. The coefficient

[11] In Panel C of Table IA7 in the Internet Appendix, we show that more foreign top VCs are mainly concentrated in VCs based in the country same as migrant founders' home country.

on *Migrant_Native*, however, is positive and significant at the 1% level, implying that the number of grant patents filed by migrant-native startups is 117% (=100 $\times$ ($e^{0.778} - 1$)) more than those by migrant-only ones and 28.3% (=100 $\times$ ($e^{0.778-0.529} - 1$)) more compared to native-only startups.

In column (2), we focus on granted patents filed specifically within the US. The coefficient on *Migrant* remains negative and statistically significant (-0.456, significant at the 10% level), suggesting that migrant-only startups have fewer patents filed in the US compared to native-only startups. However, migrant-native co-founded startups show a positive and significant effect, with the coefficient on *Migrant_Native* being 0.629 (significant at the 1% level). This indicates that the number of granted patents filed in the US by migrant-native startups is 86% (=100 $\times$ ($e^{0.622} - 1$)) higher than migrant-only startups and 18% higher than native-only startups.. Column (3) shifts the focus to patents filed outside the US. The results show that conditional on having US patents granted, the coefficient on *Migrant* shows no statistical significance, indicating no strong evidence that migrant-only startups are more or less likely to file foreign patents than native-only startups. However, the coefficient on *Migrant_Native* is positive and significant (0.910, significant at the 1% level), suggesting that migrant-native co-founded startups file more patents abroad compared to native-only startups. Columns (4) to (6) report OLS estimates where the dependent variable is an indicator for whether the startups filed at least one patent that is eventually granted. The OLS results are in line with the Poisson results.

In summary, the results in Table 6 highlight key differences in patenting activity between migrant-only and migrant-native co-founded startups. While migrant-only startups lag behind native-only startups in patent filings, particularly within the US, migrant-native co-founded startups consistently outperform both groups, filing more patents overall, in the US, and abroad. This suggests that combining the strengths of both migrant and native founders offers substantial advantages in innovation and international market expansion.

4.2 Heterogeneous effects: skilled labor availability and top VC access

Next, we examine the heterogeneous effects of migrant founders on startup performance, focusing on two key dimensions: (1) local availability of college-educated labor from founders' home countries and (2) local access to top VCs from those countries. Our previous analysis suggests that native-migrant startups, relative to migrant-only and native-only startups, leverage both migrant and native labor pools, as well as foreign and domestic VC markets. Building on this, we investigate whether the superior performance of native-migrant startups is further amplified in state-industries where they have better access to both domestic and foreign labor and VC markets.

Panel A of Table 7 examines whether the performance of migrant-native startups is higher in a state-industry with a strong presence of both native college-educated workers and migrant college-educated workers from the founders' home country. Two key independent variables of interest are: *H_Labor_Native* and *H_Labor_Origin*. *H_Labor_Native* is an indicator for state-industries with a share of native college-educated labor ranked in the top tercile each year. This share is calculated as the number of college-educated native employees in a state-industry-year divided by the total number of native college-educated workers in that state-year.

Similarly, *H_Labor_Origin* is an indicator that is equal to one for a migrant-founded startup if the share of migrant employees from the migrant founder's home country ranks in the top tercile each year. This share is calculated by dividing the number of migrant college-educated employees from a specific country in a state-industry-year by the total number of migrant college-educated workers from that country in the state-year. For example, in 2010 for Indian workers, information technology in California and Texas, and financial services in New Jersy, New York, and Connecticut are ranked in the top tercile. In addition, *H_Labor_Origin* is zero for native-only startups, as migrant workers, by definition, have different country of origins than native founders. If a startup has multiple migrant founders from different home countries, we use the country with the highest share.

The triple interaction term, *Migrant_Native*×*H_Labor_Native*×*H_Labor_Origin*, in Panel A of Table 7 is the variable of interest. The coefficients on that term are positive and statistically significant at 5% level in columns (1), (3), and (4), suggesting that within migrant-native startups, employment growth, funding amount, and the chance of getting acquired are higher if both native and migrant skilled labor from the founder's country of origin are well-represented in the startup's state-industry. Intuitively, the ability of migrant-native startups to source high-quality native and migrant labor, as shown in Table 4 , is particularly useful in those state-industries where both native and origin-country migrant labor pools are important.

Panel B of Table 7 examines whether the superior performance of migrant-native startups is enhanced when they operate in a state-industry with a strong presence of both domestic and foreign Top VCs (defined by the number of exits) from the founders' home country. Two key independent variables of interest are: *H_TopVC_Native* and *H_TopVC_Origin*. *H_TopVC_Native* is an indicator for state-industries with a share of domestic Top VCs ranked in the top tercile each year. This share is calculated as the number of domestic Top VCs that invest in firms in a state-industry-year divided by the total number of domestic Top VCs that invest firms in that state-year. *H_TopVC_Origin* is an indicator equal to one for a migrant-founded startup if the share of foreign Top VCs from the migrant founder's home country ranks in the top tercile each year. This share is calculated by dividing the number of foreign Top VCs based in a specific country that invest in firms in a state-industry-year by the total number of foreign Top VCs from that country that invest in firms in the same state-year. Similar to *H_Labor_Origin*, *H_TopVC_Origin* is zero for native-only startups. If a startup has multiple migrant founders from different home countries, we use the country with the highest share.

The results in panel B of Table 7 present patterns similar to those in Panel A. The triple interaction term, *Migrant_Native*×*H_TopVC_Native*×*H_TopVC_Origin*, is positively associated with greater employment size (coefficient: 0.338, significant at the 10% level), increased funding likelihood (coefficient: 0.1, significant at the 10% level), and more funds raised (coefficient: 0.57, significant at the 5% level). These results highlight that migrant-native startups tend to perform better in state-industries where both domestic funding and funding from the founder's origin country are important.

Our results in Table 7 highlight the critical role of both labor market composition and venture capital access in shaping the performance of native-migrant startups. These findings imply that native-migrant startups thrive in ecosystems that provide complementary resources from both home and host countries, reinforcing the idea that their advantage stems from their ability to bridge multiple networks.

4.3 Heterogeneous effects: skill complementarity and ethnic ties

In this section, we conduct two additional heterogeneity tests. The first examines whether the composition of the founding team in terms of skill diversity (e.g., engineering vs. marketing) contributes to the superior performance of native-migrant startups. One possible explanation for their outperformance relative to migrant-only or native-only startups is that native-migrant founding teams possess a broader range of skills, enhancing their ability to navigate both technical and business challenges.

Panel A of Table IA8 in the Internet Appendix supports this idea by showing that migrant entrepreneurs are more likely to have backgrounds in engineering or science compared to native founders before launching their ventures. As a result, native-migrant startups are more likely to form founding teams that combine both technical and business expertise. This pattern is further illustrated in Figure IA3 in the Internet Appendix, which depicts the skill composition of founding teams. A founder's skill is classified into seven categories-marketing, finance, administration, sales, operations, engineering, and science-using data from Revelio Labs. These are then grouped into two broad categories: business-related skills (marketing, finance, administration, sales, and operations) and tech-related skills (engineering and science).

Figure IA3 reveals that 28% of native-only startups have mixed-skill founding teams (i.e., teams that include both business- and tech-oriented co-founders). This share rises to 39% for migrant-only startups and reaches 44% for native-migrant startups, suggesting that greater skill diversity may be one of the key drivers of their superior performance.

In Panel B of Table IA8 in the Internet Appendix, we conduct heterogeneity tests to see whether the superior performance of native-migrant startups is enhanced with a tech-business founding team. However, across all five performance measures, we do not find any evidence suggesting that having a mixed tech-business founding team enhances startup performance. This indicates that while native-migrant startups are more likely to have diverse skill sets among their founders, this factor alone does not appear to be the primary driver of their outperformance.

The second heterogeneity test explores whether the performance of migrant-native startups with founders sharing same ethnicity is different from migrant-native team with diverse ethnicities. We classify ethnicity using two methods: one from Revelio Labs, which categorizes individuals into five broad ethnic groups (Asian, Black, Hispanic, Native, and White), and another from the machine learning algorithm EthnicSeer, which predicts ethnicity based on full names across 12 categories (Middle-Eastern, Chinese, English, French, Vietnamese, Spanish, Italian, German, Japanese, Russian, Indian, and Korean).

Figure IA4 in the Internet Appendix illustrates the proportion of startups with founding teams that share the same ethnicity, separately for native-only, migrant-only, and native-migrant startups. Regardless of the classification method, native-migrant startups are less likely than either migrant-only or native-only startups to have homogenous-ethnicity founding teams.

Panel A of Table IA9 in the Internet Appendix confirms this pattern, showing that migrant-native startups are 18% less likely than migrant-only startups and 9% less likely than native-only startups to have same-ethnicity founding teams. In Panel B, we test whether ethnic ties within the founding team lead to differential startup performance by interacting *Same_Ethnicity*, an indicator variable, with both *Migrant* and *Migrant_Native*. The results provide no evidence that shared ethnic backgrounds among co-founders lead to differential performance, suggesting that the success of native-migrant startups is not affected by ethnic diversity.

In summary, we conduct two heterogeneity tests to further explore the drivers of native-migrant synergies. The first examines whether skill diversity within the founding team contributes to their advantage. The second test investigates whether the ethnic diversity within founding teams affects native-migrant synergies. However, our findings suggest that neither factor explains the superior performance of native-migrant startups.

5 Instrumental Variable Approach

Our baseline results show that migrant-native co-founded startups outperform both native-only and migrant-only counterparts. However, this advantage could stem from homophily preferences (McPherson, Smith-Lovin, and Cook 2001), which may lower the entry threshold for native-only or migrant-only startups. As a result, migrant and native entrepreneurs who choose to co-found a venture may be more selective, focusing on high-potential projects that justify the additional challenges they face. Similarly, higher-quality entrepreneurs may select into migrant-native teams. To address such potential endogeneity concerns, we employ an instrumental variable approach to assess the robustness of our conclusions.

5.1 Instrumental variable (IV) construction

To capture plausibly exogenous variation in migrant (native) founders co-founding startups with natives (migrants), we explore variation in the proportion of native students among those who obtained their highest degree from the same US university, enrolled around the same year, and earned the same degree. Specifically, for an entrepreneur i who obtained the highest degree d (Bachelor, Master, MBA, Doctor provided by Revelio Lab) before establishing a startup at the US university u with enrollment year t, we calculate the following leave-one-out native students share:

$$Cohort\_Native\_Share_{i,u,d,t} = \frac{1}{3}\sum_{t=t-1}^{t=t+1} \frac{Native_{u,d,t} - \mathbb{1}\{Native\ Founder_i\}}{Native_{u,d,t} + Foreign_{u,d,t} - 1}, \tag{2}$$

where $Native_{u,d,t}$ is the number of native students who obtained degree d at the US university u with enrollment year t and $Foreign_{u,d,t}$ is the number of international students who obtained degree d at the US university u with enrollment year t. In Panel A of Table 8, the sample average of *Cohort_Native_Share* is 0.91, which is in line with international students constituting about 5% of the US college graduates as reported by the Institute of International Education.[12]

The predictive power of our IV primarily comes from a strong tendency for individuals to co-found startups with others in the same university-degree program. In Panel A of Table 8, we show that for startups with at least two co-founders, about 31% of them have co-founders who obtained their highest degrees from the same US university. Moreover, conditional on attending the same university, 89% of startups' founders enrolled in the same year, and 93% obtained the same degree. Once attending the same university, it is this strong tendency for entrepreneurs to collaborate with others in the same degree program and same enrollment year that justifies our IV construction.

To mitigate concerns that variation in student composition may be confounded by institutional quality, degree level, or cohort-specific factors, we control for university-by-degree and enrollment year fixed effects in our subsequent 2SLS estimates. This adjustment ensures that we are comparing students pursuing the same type of degree at the same university and entering in the same year. As such, we eliminate mechanical comparisons between, for instance, elite and non-elite institutions, graduate and undergraduate programs, or students entered in different years that could otherwise correlate with both team formation and startup outcomes.

To further strengthen the exogeneity of the native student share, we later implement a shift-share design that uses the pre-determined share of native students in a given university-degree program from 1995 to 1999, prior to our estimation period, and interact this with national trends in degree specific enrollment. The shift-share design ensures that the variation in native student share stems from country-level fluctuations in the total number of students pursuing a particular degree at any US university.

5.2 Two-stage least square (2SLS) results

The sample for 2SLS estimation excludes entrepreneurs who did not obtain degrees from the US universities and consists of startups with at least two co-founders. Specifically, we estimate the following 2SLS specification:

[12] For more information, please see https://opendoorsdata.org/data/international-students/enrollment-trends/

$$Migrant\_Native_{i,j,t} = \beta Cohort\_Native\_Share_i + \mathbf{\Gamma}'\boldsymbol{X}_{i,j,t} + \alpha_{j,t} + Edu\ FE + \varepsilon_{i,j,t} \tag{3}$$
$$Performance_{i,j,[t,t+\tau]} = \beta \widehat{Migrant\_Native}_{i,j,t} + \mathbf{\Gamma}'\boldsymbol{X}_{i,j,t} + \alpha_{j,t} + Edu\ FE + \varepsilon_{i,t} \tag{4}$$

The instrumental variable $Cohort\_Native\_Share_{i,j,t}$ is at the startup-founder level. The variable $\alpha_{j,t}$ denotes the Industry×Establishment Year fixed effects and $\boldsymbol{X}_{i,j,t}$ represent a set of founder-level and firm-level control variables. *Edu FE* represents University×Degree fixed effects, which correspond to a founder's degree type of the highest degree obtained at a US university.

We estimate equations (3) and (4) separately for two distinct samples: 1) startups with at least one migrant founder and 2) startups with at least one native founder. We split the sample because with a single instrumental variable, we cannot jointly estimate the 2SLS coefficients for both the *Migrant* and *Migrant_Native* variables. Dividing the analysis into two samples does not affect the comparisons. In the first sample, we compare startups co-founded by migrant and native founders with those founded solely by natives. In the second sample, we compare startups co-founded by migrants and natives with those founded exclusively by migrants.

In addition, the first-stage predictions of the 2SLS differ significantly between migrant and native founders. For migrant entrepreneurs, a higher share of native students predicts a greater likelihood of co-founding with natives. Conversely, for native founders, a higher native student share predicts a lower probability of co-founding with migrant entrepreneurs.

5.2.1 Migrant-native vs. native-only startups

Panels B and C in Table 8 report the 2SLS results for the comparison between migrant-native and native-only startups. Column (1) in Panel B presents the first-stage estimates. The coefficient on the IV, *Cohort_Native_Share*, is -0.761 and statistically significant at the 1% level. This result indicates that a higher proportion of native students in a university cohort decreases the likelihood of native founders to co-found a startup with migrant founders. In Panel A of Figure IA5 in the Internet Appendix, we also plot the binned scatterplot for the first stage results, indicating a strong negative linear relationship. The strength of the instrument is further confirmed by the Wald F-statistics, which is 138, exceeding the conventional threshold of ten for instrument relevance. Thus, the IV is unlikely to be subject to weak instrument concerns.

Columns (2) through (6) in Panel B report the corresponding 2SLS estimates. In column (2), the outcome variable is the logarithm of employment size three years after the startup's establishment, which serves as a proxy for firm growth and success. The coefficient on the predicted value of *Migrant_Native* is 0.444 (significant at the 10% level), suggesting that migrant-native startups exhibit about a 44% larger employment size after three years, relative to native-only startups. The outcome variable in column (3) is the probability of receiving external funding within three years of startup establishment. The instrumented coefficient on *Migrant_Native* is 0.355, significant at levels 1%, implying that migrant-native co-founded startups are approximately 26 percentage points more likely to secure funding within three years of establishment than native-only startups. Column (4) presents the 2SLS estimates for the impact of migrant-native co-founding on the amount of external funding raised within three years of startup establishment, as measured by the natural logarithm of funding raised plus one. The result shows a positive and significant relationship, with $\widehat{Migrant\_Native}$ having a coefficient of 1.287 (significant at the 1% level), implying that migrant-native co-founded startups raise substantially more funding than native-only startups.

Columns (5) and (6) report 2SLS regressions estimating the effect of migrant-native co-founding on the likelihoods of getting acquired within five years of establishment and the probability that a startup goes public within ten years of establishment. The 2SLS estimates for $\widehat{Migrant\_Native}$ in both of the columns show no statistically significant relationship between migrant-native-co-founding and the likelihood of getting acquired and going public, likely due to low variation in these rare outcomes, which limit the precision and power of the estimates.

Panel C of Table 8 presents second-stage estimates that examine whether having a migrant co-founder has advantages over native-only startups in accessing migrant labor pools, foreign VC networks, and overseas product markets. In column (1), the outcome variable is the share of migrant employees. The coefficient on $\widehat{Migrant\_Native}$ is 0.43, statistically significant at 1% level, suggesting that the share of migrant employees within the first five years of the inception for migrant-native startups is about 0.4 higher than that of native-only startups.

In column (2), the outcome variable is the share of promotions for migrant employees, defined in Section 4.1.1 as a proxy for labor quality. The coefficient on $\widehat{Migrant\_Native}$ is positive (0.845) and statistically significant at 1% level, indicating that migrant-native startups are able to hire more high-quality migrant workers than native-only startups. In column (3), we look into whether migrant-native startups are more likely to receive financing from non-US (foreign) VCs during the first five years of the firm inception. The second-stage estimate for instrumented variable shows that migrant-native startups are about 26% more likely to receive foreign-VC funding than native-only ones. The point estimate is statistically significant at 1% level.[13]

[13] Table IA10 in the Internet Appendix presents 2SLS estimates for alternative promotion and top VC measures.

In column (4), the outcome variable is the logarithm of one plus the number of top foreign VCs as a proxy for investor quality. We find that having a migrant co-founder, relative to native-only startups, also attracts more top foreign VCs. In column (5), we investigate whether having a migrant co-founder improves the chance of filing a patent in the non-US countries than startups with native founders only. The coefficient on $\widehat{Migrant\_Native}$ is positive but statistically insignificant, which might be due to low power since filing patents overseas is not common in our sample firms.

Overall, the 2SLS results demonstrate that migrant-native startups, compared to native-only startups, experience significantly higher employment growth, are more likely to secure funding within three years of establishment, and raise a significantly larger amount of funding. Moreover, for native entrepreneurs, having a migrant co-founder significantly improves their access to migrant labor pools and foreign VC networks.

5.2.2 Migrant-native vs. migrant-only startups

Panels D and E in Table 8 report the 2SLS results for the comparison between migrant-native and migrant-only startups. Column (1) in Panel D presents the estimates of the first-stage. The coefficient on the IV, *Cohort_Native_Share*, is 1.063 and statistically significant at the 1% level. This result indicates that a higher proportion of native students in a university cohort increases the likelihood of migrant founders to co-found a startup with natives. In Panel B of Figure IA5 in the Internet Appendix, we also plot the binned scatterplot for the first stage results, indicating a strong positive linear relationship. The strength of the instrument is further confirmed by the Wald F-statistics, which is 110, exceeding the conventional threshold of ten for instrument relevance. Thus, it is again unlikely that the IV is subject to a weak instrument issue.

Columns (2) through (6) in Panel D report the corresponding 2SLS estimates for our five startup performance measures. The 2SLS results show statistically significant (at 1% or 5% level) effects of $\widehat{Migrant\_Native}$ on employment size, funding amount, and IPO probability. Specifically, we find that migrant-native startups, compared to migrant-only startups, exhibit higher employment growth, raise more funding, and are more likely to go public.

Panel E of Table 8 presents the second-stage estimates to examine whether having a native co-founder has advantages over migrant-only startups in accessing native labor pools, domestic VC networks, and local product markets. In column (1), the outcome variable is the share of native employees. The coefficient on $\widehat{Migrant\_Native}$ is positive (0.426), statistically significant at 1% level, suggesting that the share of native employees for migrant-native startups is 42.6% higher than that of migrant-only startups.

In column (2), the outcome variable is the share of promotions for native employees, defined in section 4.1.1 as a proxy for native labor quality. The coefficient on $\widehat{Migrant\_Native}$ is positive (0.107) and statistically significant at 5% level, indicating that migrant-native startups are able to hire more high-quality native workers than migrant-only startups.

In column (4), the outcome variable is the logarithm of one plus the number of domestic top VCs (defined by the number of exits) as a proxy for investor quality. We find that having a native co-founder, relative to native-only startups, also attracts more domestic top VCs. In column (5), we also find that migrant-native startups, compared to migrant-only startup, are 14.1% more likely (significant at 10% level) to file a patent in the US that is eventually granted.[14]

Overall, the 2SLS results show that migrant-native startups, compared to migrant-only startups, experience significantly higher employment growth, raise a significantly larger amount of funding, and are more likely to go public. Moreover, for migrant entrepreneurs, having a native co-founder significantly enhances their access to native labor pools, domestic VC networks, and local product markets.

5.3 Instrument Balance, Placebo Tests, and Alternative Shift-Share Design

While our baseline 2SLS design addresses concerns related to the selection of entrepreneurs into native-migrant teams, a potential endogeneity concern of our approach is that the native share of a university-degree program may be influenced by unobserved local factors, such as local industry conditions, which might also impact native-migrant startup success. We address this concern by assessing instrument balance, constructing a placebo, and implementing an alternative, more stringent shift-share design to construct our instrument.

First, Table IA11 in the Internet Appendix presents evidence that our instrument is balanced along multiple dimensions of the local economy. Specifically, a variety of local economic conditions at state level, including local GDP growth, VC financing growth, job creation growth, new firm entry growth, and firm exit rates, are not correlated with the average value of our IV across universities within a state-year.

[14]Table IA10 of the Internet Appendix shows that native-migrant teams source higher-quality workers on average than native-only startups, as measured by external promotions. They also work with more top VCs on average, as measured by both exits and number of deals. Table IA10 further shows that relative to migrant-only startups, native-migrant startups work with higher-quality native workers, as measured by both internal and external promotions. They also work with more top VCs on average and more top domestic VCs, as measured by the number of exits.

Second, to the extent that our instrument is correlated with unobserved local economic conditions that also predict native-migrant entrepreneurial outperformance , we would expect such conditions would also predict native-only and migrant-only success. This reasoning motivates a placebo test in which we examine whether our IV is associated with the performance of migrant-only or native-only startups. Reasurringly, the results of the placebo test, reported in Table IA12 in the Internet Appendix, show no significant relationship between our IV and the performance of migrant-only or native-only startups across all five performance measures.

Finally, to further address concerns that the share of native students may be correlated with unobserved local factors that could influence the future performance of native-migrant startups, we estimate an alternative shift-share specification. Specifically, we first measure the average share of native students in a given university-degree program from 1995 to 1999, a five-year window preceding the start of our sample period. We then interact this variable with the total number of US natives pursuing a particular degree in a given year across all universities. In this way, time-series variation in the IV at the university-degree level is unlikely to be correlated with regional unobserved factors that could influence future native-migrant startup success.

We follow Card (2009) and define the share of students from the country c at the US university u who obtained degree d between 1995 and 1999 as follows:

$$Share_{c,u,d,[1995,1999]} = \frac{Enroll_{c,u,d,[1995,1999]}}{Enroll_{c,d,[1995,1999]}}, \tag{5}$$

where $Enroll_{c,u,d,[1995,1999]}$ is the number of students from country c who enrolled at the US university u with degree d between 1995 and 1999 and $Enroll_{c,d,[1995,1999]}$ represents the total number of students from country c who enrolled at any US university with a degree d between 1995 and 1999.

With these pre-determined shares, for a given US university u, degree d, and an enrollment year t, we then define the following shift-share instrument:

$$Shift\_Share_{u,d,t} = \frac{Enroll_{US,d,t} \times Share_{US,u,d,[1995,1999]}}{\sum_c Enroll_{c,d,t} \times Share_{c,u,d,[1995,1999]}}, \tag{6}$$

where $Enroll_{US,d,t}$ in the numerator is the total number of native students who enrolled in degree d in year t and $Share_{US,u,d,[1995,1999]}$ is the share defined in equation (5) for native students.

The 2SLS results using this alternative instrumental variable are reported in Table 9. Consistent with our previous tests, the estimates are qualitatively and quantitatively similar to those reported in Table 8 where the IV is based on the contemporaneous share of native students enrolled in a given US university-degree program.

5.4 Magnitude of estimates: 2SLS vs. OLS

In this subsection, we discuss two potential reasons for why the 2SLS estimates are larger than the OLS estimates. Note first that the sample used for the 2SLS estimate focuses on US college-educated entrepreneurs and is at the startup-founder level, which differs from the sample used in the baseline OLS estimation. To directly compare OLS estimates with 2SLS estimates, in Panel A of Table IA4, we also report OLS estimates using the same sample as that used for the 2SLS analysis. Overall, the results confirm that the 2SLS estimates are larger than the OLS estimates across ten specifications in Panel A of Table IA4.

The first potential explanation for this difference is that the 2SLS estimates a local average treatment effect (LATE). The compliers of our IV are, by construction, entrepreneurs who enrolled in the same university degree program. It is possible that a native-migrant founding team with all founders from the same university-degree program leads to better startup performance. To test this possibility, we perform heterogeneity tests in the baseline OLS regressions controlling for whether all the founders in a native-migrant startup graduated from the same university or obtained the same type of degree. The results of these heterogeneity tests are reported in Table 10. For employment size, funding likelihood, and funding amount, native-migrant startups with founders from the same university with the same degree perform significantly better than those native-startups with founders from different university or degree programs. These results suggest that larger 2SLS estimates could be due to the LATE. Particularly, when comparing native-migrant startups to native-only ones for employment size in Panel A of Table 10, the coefficient on interaction term, *Migrant_Native*$\times$*Same_UDY*, is 0.15, suggesting that native-migrant startups with founders from the same cohort is 15% larger than native-migrant startups with founders from different university programs. Moreover, compared to native-only startups, native-migrant startups with founders from the same cohort are 35% larger. This magnitude is almost identical to that of 2SLS shown in Table 8, which is 33%. For the effects on two funding outcomes that are estimated in this heterogeneity test, though they are still smaller than the counterparts estimated in 2SLS, but they are 50%-70% larger than those estimated in baseline OLS regressions.

The second potential reason that the OLS estimates could be downward biased relates to founders' outisde options. In particular, since migrants earn less than natives with similar observed characteristics (e.g., Dostie et al. 2023), they may choose a lower threshold for selecting projects that they are willing to work on. If that is the case, the OLS estimates would be downward biased and the 2SLS estimates will be larger. To test this, we estimate founders' reservation wage or the values of outside option to see whether in lieu of starting a startup, migrants have worse outside options. The details of estimating the value of the outside option are described in Section IA.2 in the Internet Appendix. In column (1) of Table IA13, we confirm the native-migrant pay gap documented in the literature by showing that migrant founders, relative to native founders enrolled in the same university degree program during the same enrollment year, exhibit lower value outside options. More importantly, in columns (2) to (6), we repeat the baseline regressions, reported in Table 3. Once the value of founders' outside options is controlled for, the coefficients on *Migrant_Native* are significantly larger in four out of five startup performance measures, suggesting that the baseline OLS measures are in fact downward biased.

5.5 Extensive Margin

We have thus far examined the performance of startups conditional on establishment. A natural and policy-relevant question is whether the migrant mix in a university-degree program is associated with the total rate of startup creation. In this final subsection, we study the relationship between our instrument, that is the share of native students in a degree program in a given enrollment year, and the percentage of students from that cohort who co-found a startup. The results are reported in Table IA14 in the Internet Appendix. In column (1), the dependent variable is the number of all co-founders who graduate from a university-degree-year, scaled by the total number of graduates in that university-degree-year. The coefficient on *Share of Native Students* is insignificant, suggesting that the share of native students for a given university-degree-year does not affect the cohort share of co-founders. Columns (2) through (4) disaggregate co-founders by type: 1) migrant founders who co-found with natives, 2) migrants who co-found with migrants, and 3) natives who co-found with natives. We find that the share of native students are negatively correlated with the share of migrant founders who either co-found with natives or with migrants, but positively associated with the share of native founders who co-found with natives. These results suggest that native student share influences the relative composition of co-founders (migrant vs. native), but does not change the total number of co-founders.

As a final test, we examine whether the university-degree-year native share impacts the propensity of native and migrant students to co-found a company. In columns (5) and (6) of Table IA14 we therefore test whether our IV is correlated with the probability that migrants or natives within the cohort co-found a company, as measured by the share of migrant (native) co-founders divided by the total number of migrant (native) students in the cohort. Column (5) reports the results for migrants and column (6) reports the results for natives. In both cases, we find no significant relationship between the native share and the propensity to co-found a company. These results imply that the change in startup composition due to degree program native shares is not driven by changes in the likelihood by either migrants or natives to start a company, but is driven instead by the identity of their co-founders.

6 Conclusion

This paper examines the performance of startups co-founded by immigrant and native entrepreneur teams, relative to those startups founded solely by US-born or immigrant entrepreneurs. Using a dataset constructed from Crunchbase and Revelio Labs, we link startups to the employment and education histories of its founders and employees. We find that native-migrant teams tend to outperform their native-only and migrant-only counterparts, being 20% larger in employment three years post-inception, more likely to secure funding, accessing larger funding rounds, and more likely to achieve a successful exit through either acquisition or IPO.

To establish causality, we develop an instrumental variables strategy that leverages the native share in university degree programs attended by native startup founders. Our 2SLS findings indicate that startups with native-migrant teams are approximately 50% larger and 24% more likely to receive funding than native-only startups. We explore mechanisms driving this outperformance, identifying access to a diverse labor pool, foreign investors, and overseas markets as key factors. Various heterogeneity tests provide further evidence supporting these underlying mechanisms.

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Figure 1: Migrant Entrepreneurs in the US

This figure presents the percentage of migrant entrepreneurs, the top ten countries of origin for migrant entrepreneurs, and the top ten industries in which firms were established by migrants. *Single_Founder* indicates migrant entrepreneurs who establish startups without co-founding with others. *Migrant_Native* indicates migrant entrepreneurs who co-found startups with native entrepreneurs. *Same_Origin* indicates migrant entrepreneurs who co-found startups with migrant entrepreneurs from the same country of origin. *Mixed_Origin* indicates migrant entrepreneurs who co-found startups with migrant entrepreneurs from the different countries of origin. Panel A shows the percentage of migrant entrepreneurs over all entrepreneurs who established startups in the US in each year from 2000 to 2022. Panel B displays the top ten countries of origins for migrant entrepreneurs. The top ten countries are selected by the number of startups migrant founders established in the US from 2000 to 2022. Panel C plots the top ten industries where migrant entrepreneurs established startups in the US from 2000 to 2022. The top ten industries are selected by the share of migrant entrepreneurs. The industry classification is based on that of Crunchbase database.

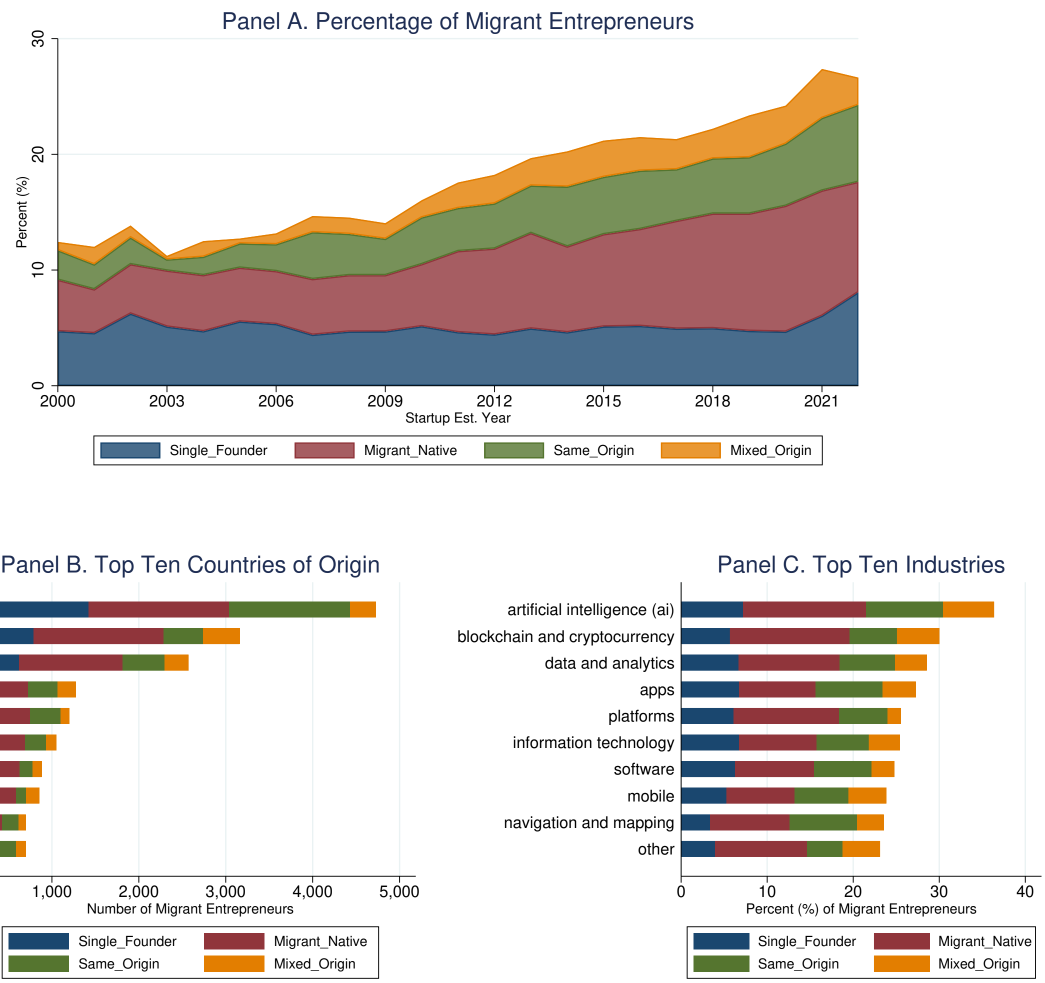

Figure 2: Migrant Employees, Foreign VCs, and the Country of Origin

This figure plots the average shares of migrant employees and foreign VCs by their countries of origin across startups in our sample. Panel A plots the shares of employees hired within the first five years of startup inception by their countries of origin. Panel B plots the shares of VC investors that invest in startups within first three years of inception by countries where they are based.

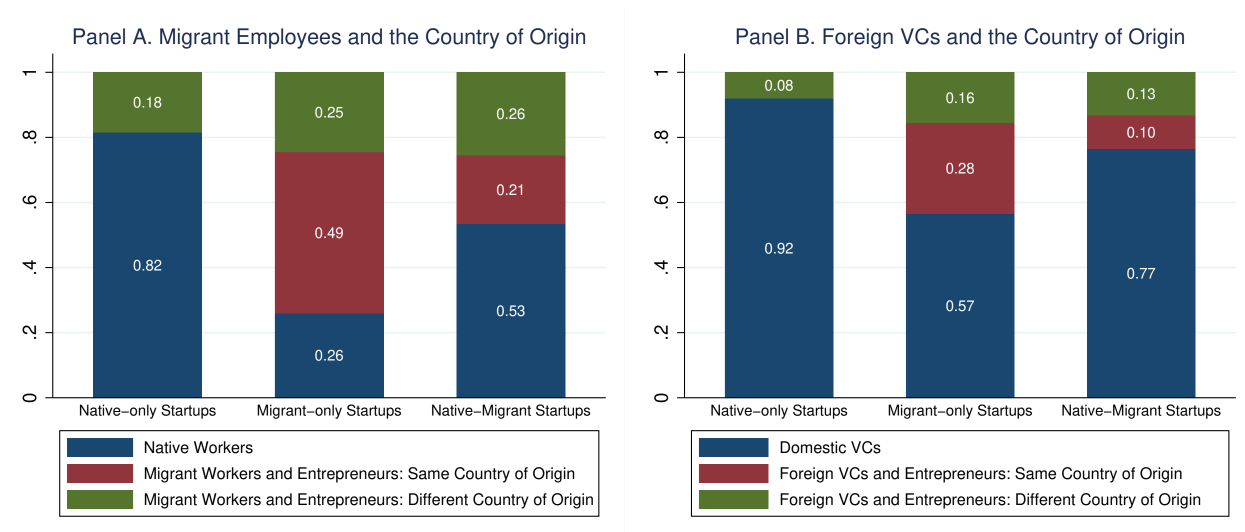

Table 1. Summary Statistics: Entrepreneur Level

This table provides the summary statistics at entrepreneurs level. The sample consists of 53,740 entrepreneurs who co-found startups with other entrepreneurs between 2000 and 2017 in the US. We compare the characteristics of native entrepreneurs with those of migrant entrepreneurs. Table A1 provides detailed variable definitions. The individual-level summary statistics including single founders are provided in Table IA1 in the Internet Appendix.

	N(Migrant)	N(Native)	μ(Migrant)	μ(Native)	Migrant - Native
Bachelor	12872	40868	0.23	0.32	-0.091***
Graduate	12872	40868	0.42	0.26	0.153***
Top10_University	12872	40868	0.04	0.06	-0.017***
Top50_University	12872	40868	0.07	0.07	-0.003
Top100_University	12872	40868	0.04	0.03	0.004**
Male	12872	40868	0.70	0.76	-0.066***
Serial_Entrepreneur	12872	40868	0.41	0.39	0.012**
Manager	12872	40868	0.51	0.49	0.011**
Experience	12872	40868	9.24	9.40	-0.164**
Exp_Engineer	12872	40868	2.83	1.88	0.949***
Exp_Finance	12872	40868	0.51	0.85	-0.340***
Exp_Marketing	12872	40868	1.43	1.71	-0.273***
Exp_Operation	12872	40868	0.99	1.02	-0.038
Exp_Sales	12872	40868	2.47	2.68	-0.215***
Exp_Scientist	12872	40868	0.77	0.62	0.152***
Observations	53740				

Table 2. Startup Level: Summary Statistics and Univariate Analyses

This table provides the summary statistics at firm level. The sample consists of 22,967 firms with at least two co-founders that were established between 2000 and 2017 in the US. Table A1 provides detailed variable definitions. The firm-level summary statistics for all startups are provided in Table IA2 in the Internet Appendix.

Panel A. Firm-level Summary Statistics

	N	Mean	Std	P1	P25	P50	P75	P99
Migrant	22967	0.33	0.47	0.00	0.00	0.00	1.00	1.00
Migrant_Native	22967	0.22	0.42	0.00	0.00	0.00	0.00	1.00
Emp_{t+3}	22967	26.10	637.33	1.00	3.00	6.00	14.00	149.00
$Mig\_Emp\_Share_{[t,t+5]}$	22967	0.30	0.33	0.00	0.02	0.17	0.50	1.00
$Raised_{[t,t+3]}$ *($MM)*	22967	44.47	309.66	0.00	0.00	0.00	3.07	855.00
$Funded_{[t,t+3]}$	22967	0.36	0.48	0.00	0.00	0.00	1.00	1.00
$Foreign\_VC_{[t,t+3]}$	22967	0.18	0.38	0.00	0.00	0.00	0.00	1.00
$All\_Top\_VC\_Deal_{[t,t+3]}$	22967	1.73	5.13	0.00	0.00	0.00	1.00	24.00
$Foreign\_Top\_VC\_Deal_{[t,t+3]}$	22967	0.23	1.17	0.00	0.00	0.00	0.00	5.00
$Domestic\_Top\_VC\_Deal_{[t,t+3]}$	22967	1.50	4.61	0.00	0.00	0.00	0.00	22.00
$All\_Top\_VC\_Exit_{[t,t+3]}$	22967	0.88	2.96	0.00	0.00	0.00	0.00	14.00
$Foreign\_Top\_VC\_Exit_{[t,t+3]}$	22967	0.08	0.53	0.00	0.00	0.00	0.00	2.00
$Domestic\_Top\_VC\_Deal_{[t,t+3]}$	22967	0.81	2.78	0.00	0.00	0.00	0.00	13.00
$Acq_{[t,t+5]}$	22967	0.06	0.23	0.00	0.00	0.00	0.00	1.00
$IPO_{[t,t+10]}$	22967	0.01	0.11	0.00	0.00	0.00	0.00	1.00
Number_Founders	22967	2.51	1.57	2.00	2.00	2.00	3.00	6.00
Bachelor	22967	0.51	0.50	0.00	0.00	1.00	1.00	1.00
Graduate	22967	0.49	0.50	0.00	0.00	0.00	1.00	1.00
Serial_Entrepreneur	22967	0.65	0.48	0.00	0.00	1.00	1.00	1.00
Manager	22967	0.74	0.44	0.00	0.00	1.00	1.00	1.00
Experience	22967	13.06	8.05	0.00	7.00	12.00	18.00	33.00
Top10_University	22967	0.10	0.30	0.00	0.00	0.00	0.00	1.00
Top50_University	22967	0.14	0.35	0.00	0.00	0.00	0.00	1.00
Top100_University	22967	0.07	0.26	0.00	0.00	0.00	0.00	1.00
$All\_Patent_{[t,t+5]}$	22967	0.55	5.76	0.00	0.00	0.00	0.00	12.00
$US\_Patent_{[t,t+5]}$	22967	0.41	4.42	0.00	0.00	0.00	0.00	9.00
$Foreign\_Patent_{[t,t+5]}$	22967	0.14	2.09	0.00	0.00	0.00	0.00	3.00
Business_Business	22967	0.59	0.49	0.00	0.00	1.00	1.00	1.00
Tech_Tech	22967	0.09	0.29	0.00	0.00	0.00	0.00	1.00
Tech_Business	22967	0.32	0.47	0.00	0.00	0.00	1.00	1.00

Panel B. Univariate Analyses

	Native-only (1)	Migrant-only (2)	Migrant-Native (3)	(3) - (1)	(3) - (2)
$Ln(Emp_{t+3})$	1.75	1.92	2.09	0.33^{***}	0.17^{***}
$Funded_{[t,t+3]}$	0.32	0.42	0.46	0.13^{***}	0.03^{**}
ln(Raised_$[t,t+3]$)	0.88	1.03	1.37	0.49^{***}	0.35^{***}
$Acq_{[t,t+5]}$	0.05	0.04	0.07	0.02^{***}	0.03^{***}
$IPO_{[t,t+10]}$	0.01	0.01	0.02	0.01^{***}	0.01^{***}
Bachelor	0.54	0.40	0.47	-0.07^{***}	0.07^{***}
Graduate	0.42	0.65	0.62	0.20^{***}	-0.03^{*}
Serial_Entrepreneur	0.63	0.66	0.72	0.09^{***}	0.06^{***}
Manager	0.72	0.74	0.79	0.06^{***}	0.04^{***}
Experience	12.83	12.06	14.21	1.38^{***}	2.15^{***}
Top10_University	0.10	0.06	0.14	0.04^{***}	0.08^{***}
Top50_University	0.13	0.11	0.17	0.04^{***}	0.06^{***}
Top100_University	0.07	0.07	0.09	0.02^{***}	0.02^{*}
Business_Business	0.65	0.46	0.47	-0.17^{***}	0.01
Tech_Tech	0.08	0.16	0.10	0.01^{**}	-0.06^{***}
Tech_Business	0.27	0.38	0.43	0.16^{***}	0.05^{***}

Table 3. Startup Performance and Migrant Entrepreneurs: OLS Estimates

This table presents effects of migrant entrepreneurs on startup performance, measured by the employment size three years after the inception year, the probability of getting funded and total funding amount three years within the startup establishment, the probability of getting acquired five years within the startup establishment, and the probability of going public ten years within the startup establishment. The sample consists of startups with at least two co-founders. For all specifications, robust standard errors are clustered at Industry×Year level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively. Table A1 provides detailed variable definitions.

	$Ln(Emp_{t+3})$		$Funded_{[t,t+3]}$		$Ln(Raised_{[t,t+3]}+1)$		$Acq_{[t,t+5]}$		$IPO_{[t,t+10]}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Migrant	0.204***	0.151***	0.052***	0.045***	0.138***	0.008	-0.006	-0.025***	0.004**	0.000
	(0.019)	(0.028)	(0.007)	(0.011)	(0.027)	(0.043)	(0.005)	(0.007)	(0.002)	(0.002)
Migrant_Native		0.079***		0.010		0.192***		0.028***		0.005*
		(0.029)		(0.013)		(0.046)		(0.008)		(0.003)
Bachelor	0.000	-0.001	0.010	0.010	0.002	-0.001	0.006	0.005	-0.001	-0.001
	(0.019)	(0.019)	(0.007)	(0.007)	(0.025)	(0.025)	(0.005)	(0.005)	(0.001)	(0.001)
Graduate	0.044**	0.046***	0.054***	0.054***	0.157***	0.161***	0.002	0.003	0.002	0.002
	(0.017)	(0.018)	(0.007)	(0.007)	(0.027)	(0.027)	(0.005)	(0.005)	(0.001)	(0.001)
Serial_Entrepreneur	0.193***	0.192***	0.078***	0.077***	0.298***	0.296***	0.017***	0.017***	0.003**	0.003*
	(0.018)	(0.018)	(0.007)	(0.007)	(0.025)	(0.025)	(0.005)	(0.005)	(0.002)	(0.002)
Manager	0.218***	0.218***	0.067***	0.068***	0.259***	0.260***	0.033***	0.033***	0.004***	0.004***
	(0.019)	(0.019)	(0.007)	(0.007)	(0.028)	(0.028)	(0.005)	(0.005)	(0.002)	(0.002)
Experience	0.005***	0.004***	-0.001	-0.001	0.005***	0.004***	0.001**	0.001**	0.001***	0.001***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Top10_University	0.330***	0.325***	0.175***	0.175***	0.932***	0.920***	0.058***	0.056***	0.016***	0.015***
	(0.029)	(0.029)	(0.011)	(0.011)	(0.055)	(0.055)	(0.009)	(0.009)	(0.004)	(0.004)
Top50_University	0.069***	0.067***	0.074***	0.074***	0.322***	0.315***	0.031***	0.030***	0.001	0.001
	(0.023)	(0.023)	(0.009)	(0.009)	(0.037)	(0.037)	(0.007)	(0.007)	(0.002)	(0.002)
Top100_University	0.013	0.011	0.013	0.012	0.079*	0.076*	0.012	0.012	0.001	0.001
	(0.029)	(0.029)	(0.011)	(0.011)	(0.044)	(0.044)	(0.010)	(0.010)	(0.003)	(0.003)
Number_Founders	0.091***	0.090***	0.005	0.005	0.062**	0.060*	0.001	0.001	0.001	0.001
	(0.024)	(0.024)	(0.005)	(0.005)	(0.031)	(0.031)	(0.002)	(0.002)	(0.001)	(0.001)
Tech_Tech	-0.067**	-0.062**	0.100***	0.101***	0.369***	0.380***	0.041***	0.043***	-0.002	-0.002
	(0.031)	(0.031)	(0.013)	(0.013)	(0.050)	(0.050)	(0.009)	(0.009)	(0.003)	(0.003)
Tech_Business	0.004	0.004	0.143***	0.143***	0.457***	0.458***	0.044***	0.044***	0.001	0.001
	(0.021)	(0.021)	(0.008)	(0.008)	(0.031)	(0.031)	(0.006)	(0.006)	(0.002)	(0.002)
Industry × Est. Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	22912	22912	22912	22912	22912	22912	22912	22912	22912	22912
Adj. R^2	0.066	0.066	0.153	0.153	0.143	0.144	0.046	0.046	0.052	0.052

Table 4. Native and Immigrant Labor Pool

This table presents results examining whether startups with migrant founders hire more migrant employees, whether migrant founders are better at screening migrant workers, and whether native founders are better at screening native workers. Employee quality is measured by the share of workers hired within the first five years of a firm's inception who are subsequently promoted. The analysis distinguishes between promotions after employees have transitioned to other firms (external promotions) and promotions within the firm (internal promotions). The share of migrant (native) promotion is calculated by dividing the number of migrant (native) promotions by the number of migrant (native) employees. The set of control variables is the same as that in Table 3. For all specifications, robust standard errors are clustered at Industry×Year level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively. Table A1 provides detailed variable definitions.

		Share of External Promotions			Share of Internal Promotions		
	$Mig\_Emp\_Share_{[t,t+5]}$	$All_{[t,t+5]}$	$Migrant_{[t,t+5]}$	$Native_{[t,t+5]}$	$All_{[t,t+5]}$	$Migrant_{[t,t+5]}$	$Native_{[t,t+5]}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Migrant	0.548***	0.003	0.028***	-0.026***	-0.002	0.041***	-0.042***
	(0.007)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Migrant_Native	-0.277***	0.009***	0.003	0.025***	0.008**	-0.008	0.037***
	(0.008)	(0.003)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)
Controls	Y	Y	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y	Y	Y
N	22912	22912	22912	22912	22912	22912	22912
Adj. R^2	0.361	0.011	0.015	0.009	0.006	0.018	0.008
Mean of Dep. Variable	0.304	0.142	0.151	0.141	0.185	0.189	0.185

Table 5. Domestic and Foreign Investors

This table presents results examining whether startups with migrant founders are more likely to get funded by foreign VCs, whether migrant founders attract more top foreign VCs, and whether native founders attract more top domestic VCs. Top VCs are defined such that they are ranked in the top ten percentiles in terms of the number of past deals and successful exits. Column (1) presents OLS estimates with the dependent variable being an indicator equal to one if a firm is funded by foreign VCs within three years of the firm's inception, and columns (2) - (7) present Poisson estimates with the dependent variables being the number of all top VCs, foreign top VCs, or domestic top VCs that invest in the firm within the three years of its inception. The set of control variables is the same as that in Table 3. For all specifications, robust standard errors are clustered at Industry×Year level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively. Table A1 provides detailed variable definitions.

		Number of Top VCs by Deals			Number of Top VCs by Exits		
	$Foreign\_VC_{[t,t+3]}$	$All_{[t,t+3]}$	$Foreign_{[t,t+3]}$	$Domestic_{[t,t+3]}$	$All_{[t,t+3]}$	$Foreign_{[t,t+3]}$	$Domestic_{[t,t+3]}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Migrant	0.113***	-0.090	1.457***	-0.451***	-0.193***	1.099***	-0.365***
	(0.010)	(0.063)	(0.097)	(0.070)	(0.072)	(0.127)	(0.076)
Migrant_Native	-0.036***	0.215***	-0.418***	0.453***	0.339***	-0.247**	0.449***
	(0.012)	(0.069)	(0.087)	(0.079)	(0.080)	(0.121)	(0.085)
Controls	Y	Y	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y	Y	Y
N	22912	21726	19161	21659	21194	16185	21108
Adj. R^2	0.099						
Pseudo R^2		0.173	0.183	0.172	0.164	0.145	0.163

Table 6. Domestic and Overseas Patenting

This table investigates startups' overall patenting activities as well as the patenting activities in non-US countries and the US separately. Columns (1) to (3) report Poisson estimates with the dependent variables being the number of granted patents field within the first five years of startups' inception. The dependent variables in columns (1) to (3) are the number of granted patents field within the first five years of startups' inception. Columns (4) to (6) report OLS estimates with the dependent variables being the indicator that is equal to one if at least one granted patent field within the first five years of startups' inception. The set of control variables is the same as that in Table 3. For all specifications, robust standard errors are clustered at Industry×Year level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively. Table A1 provides detailed variable definitions.

	Number of Patents (Poisson)			Indicator (OLS)		
	$All_{[t,t+5]}$	$US_{[t,t+5]}$	$Foreign_{[t,t+5]}$	$All_{[t,t+5]}$	$US_{[t,t+5]}$	$Foreign_{[t,t+5]}$
	(1)	(2)	(3)	(4)	(5)	(6)
Migrant	-0.529**	-0.456**	-0.428	-0.029***	-0.028***	-0.003
	(0.209)	(0.224)	(0.352)	(0.005)	(0.005)	(0.002)
Migrant_Native	0.778***	0.629***	0.939***	0.029***	0.028***	0.007**
	(0.215)	(0.219)	(0.364)	(0.006)	(0.006)	(0.003)
$\text{US\_Patent}_{[t,t+5]}$			4.541***			0.243***
			(0.393)			(0.012)
Controls	Y	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y	Y
N	19262	19090	10817	22912	22912	22912
Pseudo R^2	0.338	0.311	0.664			
Adj. R^2				0.116	0.106	0.295

Table 7. Heterogeneous Effects: Skilled Labor Availability and Top VC Access

This table presents results examining whether superior performance of migrant-native startups is enhanced in state-industries where they have better access to both domestic and foreign labor and VC markets. In Panel A, *H_Labor_Native* is an indicator for state-industries with a share of native college-educated labor ranked in the top tercile each year. This share is calculated as the number of college-educated native employees in a state-industry-year divided by the total number of native college-educated workers in that state-year. *H_Labor_Origin* is an indicator equal to one for a migrant-founded startup if the share of migrant employees from the migrant founder's home country ranks in the top tercile each year. This share is calculated by dividing the number of migrant college-educated employees from a specific country in a state-industry-year by the total number of migrant college-educated workers from that country in the state-year. In Panel B, *H_TopVC_Native* is an indicator for state-industries with a share of domestic Top VCs ranked in the top tercile each year. This share is calculated as the number of domestic Top VCs that invest in firms in a state-industry-year divided by the total number of domestic Top VCs that invest firms in that state-year. *H_TopVC_Origin* is an indicator equal to one for a migrant-founded startup if the share of foreign Top VCs from the migrant founder's home country ranks in the top tercile each year. This share is calculated by dividing the number of foreign Top VCs based in a specific country that invest in firms in a state-industry-year by the total number of foreign Top VCs from that country that invest in firms in the same state-year. For both Panel A and B, if a startup has multiple migrant founders from different home countries, we use the country with the highest share. *Other Interactions* include: *Migrant_Native×H_Labor(TopVC)_Origin*, *Migrant_Native×H_Labor(TopVC)_Native*, and 3) *Native×H_Labor(TopVC)_Native*. Other potential interaction terms under triple interaction setting are omitted due to collinearity because *H_Labor(TopVC)_Origin* is zero for startups without migrant founders. The set of control variables is the same as that in Table 3. For all specifications, robust standard errors are clustered at Industry×Year level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively. Table A1 provides detailed variable definitions.

Panel A. Local College-Educated Labor

	$Ln(Emp_{t+3})$	$Funded_{[t,t+3]}$	$Ln(Raised_{[t,t+3]}+1)$	$Acq_{[t,t+5]}$	$IPO_{[t,t+10]}$
	(1)	(2)	(3)	(4)	(5)
Migrant	0.167***	0.046***	-0.017	-0.022**	0.005
	(0.037)	(0.015)	(0.053)	(0.010)	(0.003)
Migrant_Native	0.101**	0.004	0.206***	0.024**	-0.000
	(0.040)	(0.016)	(0.059)	(0.011)	(0.003)
H_Labor_Native	0.035	0.062***	0.352***	0.024	-0.000
	(0.047)	(0.023)	(0.082)	(0.015)	(0.004)
H_Labor_Origin	0.698**	0.155	0.966	0.185	0.032
	(0.354)	(0.146)	(0.662)	(0.136)	(0.091)
H_Labor_Native×H_Labor_Origin	-0.451	-0.149	-0.952	-0.185	-0.029
	(0.380)	(0.156)	(0.693)	(0.142)	(0.091)
Migrant_Native× H_Labor_Native×H_Labor_Origin	1.262**	0.152	2.034***	0.348**	0.061
	(0.490)	(0.208)	(0.760)	(0.145)	(0.093)
Other Interactions	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y
N	22912	22912	22912	22912	22912
Adj. R^2	0.067	0.154	0.146	0.047	0.053

Panel B. Local Top VC

	Ln(Emp$_{t+3}$)	*Funded$_{[t,t+3]}$*	*Ln(Raised$_{[t,t+3]}$+1)*	*Acq$_{[t,t+5]}$*	*IPO$_{[t,t+10]}$*
	(1)	(2)	(3)	(4)	(5)
Migrant	0.076**	0.008	-0.150***	-0.031***	0.001
	(0.037)	(0.015)	(0.049)	(0.006)	(0.003)
Migrant_Native	0.164***	0.037**	0.255***	0.029***	-0.001
	(0.042)	(0.016)	(0.056)	(0.007)	(0.003)
H_TopVC_Native	0.182**	0.097**	0.400***	0.001	0.003
	(0.078)	(0.039)	(0.144)	(0.015)	(0.008)
H_TopVC_Origin	0.176***	0.079***	0.334***	0.020**	0.002
	(0.054)	(0.022)	(0.079)	(0.010)	(0.005)
H_TopVC_Native×H_TopVC_Origin	-0.121	-0.044	-0.148	0.010	-0.011
	(0.147)	(0.063)	(0.249)	(0.027)	(0.012)
Migrant_Native× H_TopVC_Native×H_TopVC_Origin	0.338*	0.110*	0.570**	0.019	0.024
	(0.173)	(0.065)	(0.288)	(0.033)	(0.021)
Other Interactions	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y
N	22912	22912	22912	22912	22912
Adj. R^2	0.067	0.155	0.147	0.020	0.054

Table 8. Startup Performance and Migrant Entrepreneurs: 2SLS Estimates

This table presents 2SLS results at founder-startup level with the instrumental variable *Cohort_Native_Share*, defined as the share of native students among those who obtained the highest degree from the same US university, enrolled around the same year, and obtained the same degree. Panel A presents summary statistics related to the IV construction. *Same_University*, *Same_Enrollment_Year*, and *Same_Degree* are indicators that are equal to one if all of the co-founders in a startup obtained the highest degree from the same US university, obtained the highest degree from US universities with the same enrollment year, and obtained the same highest degree from US universities, respectively. The sample in Panels B and C contains the startups with at least one native co-founder, and the sample in Panels D and E include startups with at least one migrant co-founders. In Panel C (E), *Mig(Native)_Promotion*$_{[t,t+5]}$ is the share of promotions for migrant (native) employees. *Foreign(Domestic)_VC*$_{[t,t+5]}$ is a dummy variable indicating whether a firm is invested by a foreign (domestic) VC. *Foreign(Domestic)_TopVC*$_{[t,t+5]}$ is the logarithm of one plus the number of foreign (domestic) Top VCs, defined by the number of exits. *Foreign(Domestic)_Patent*$_{[t,t+5]}$ is a dummy variable indicating whether a US firm files a overseas (domestic) patent that is eventually granted. The set of control variables include *Manager*, *Experience*, *Serial_Entrepreneur*, and *Number_Founder*. For all specifications, robust standard errors are clustered at Industry×Year level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively. Table A1 provides detailed variable definitions.

Panel A. Descriptive Statistics

	Cohort_Native_Share	Same_University	Same_Enrollment_Year Cond. on Same_University=1	Same_Degree Cond. on Same_University=1
Mean	0.91	0.31	0.89	0.93

Panel B. Migrant-Native vs. Native: Performance

	First Stage	Second Stage				
	Migrant_Native	*Ln(Emp*$_{t+3}$*)*	*Funded*$_{[t,t+3]}$	*Ln(Raised*$_{[t,t+3]}$*+1)*	*Acq*$_{[t,t+5]}$	*IPO*$_{[t,t+10]}$
	(1)	(2)	(3)	(4)	(5)	(6)
Cohort_Native_Share	-0.761***					
	(0.065)					
$\widehat{Migrant\_Native}$		0.444*	0.355***	1.287***	0.018	-0.011
		(0.241)	(0.092)	(0.379)	(0.047)	(0.020)
Controls	Y	Y	Y	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y	Y	Y	Y
University×Degree FE	Y	Y	Y	Y	Y	Y
N	27601	27601	27601	27601	27601	27601
Wald F	138.8					

Panel C. Migrant-Native vs. Native: Foreign Labor, VC, and Patenting

	Second Stage				
	Mig_Emp_Share$_{[t,t+5]}$	*Mig_Promotion*$_{[t,t+5]}$	*Foreign_VC*$_{[t,t+5]}$	*Foreign_TopVC*$_{[t,t+5]}$	*Foreign_Patent*$_{[t,t+5]}$
	(1)	(2)	(3)	(4)	(5)
$\widehat{Migrant\_Native}$	0.430***	0.095*	0.263***	0.119***	0.031
	(0.061)	(0.055)	(0.076)	(0.038)	(0.027)
Controls	Y	Y	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y	Y	Y
University×Degree FE	Y	Y	Y	Y	Y
N	27601	27601	27601	27601	27601

Panel D. Migrant-Native vs. Migrant: Performance

	First Stage	Second Stage				
	Migrant_Native	*Ln(Emp*$_{t+3}$*)*	*Funded*$_{[t,t+3]}$	*Ln(Raised*$_{[t,t+3]}$*+1)*	*Acq*$_{[t,t+5]}$	*IPO*$_{[t,t+10]}$
	(1)	(2)	(3)	(4)	(5)	(6)
Cohort_Native_Share	1.063***					
	(0.101)					
$\widehat{Migrant\_Native}$		0.906**	0.155	1.492***	-0.013	0.083**
		(0.352)	(0.121)	(0.558)	(0.058)	(0.039)
Controls	Y	Y	Y	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y	Y	Y	Y
University×Degree FE	Y	Y	Y	Y	Y	Y
N	6525	6525	6525	6525	6525	6525
Wald F	110.6					

Panel E. Migrant-Native vs. Migrant: Domestic Labor, VC, and Patenting

	Second Stage				
	Native_Emp_Share$_{[t,t+5]}$	*Native_Promotion*$_{[t,t+5]}$	*Domestic_VC*$_{[t,t+5]}$	*Domestic_TopVC*$_{[t,t+5]}$	*Domestic_Patent*$_{[t,t+5]}$
	(1)	(2)	(3)	(4)	(5)
$\widehat{Migrant\_Native}$	0.426***	0.107**	0.158	0.394**	0.141*
	(0.078)	(0.045)	(0.106)	(0.186)	(0.073)
Controls	Y	Y	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y	Y	Y
University×Degree FE	Y	Y	Y	Y	Y
N	6525	6525	6525	6525	6525

Table 9. Alternative Instrumental Variable: Shift Share

This table presents 2SLS results at founder-startup level with the instrumental variable *Shift_Share*, based on the average share of native students in a given university-degree program from 1995 to 1999, a five-year window preceding the start of our sample period. The details of the IV definition are described in Section 5.3. The sample in Panels A and B contains the startups with at least one native co-founder, and the sample in Panels C and D include startups with at least one migrant co-founders. In Panel C (E), *Mig(Native)_Promotion*$_{[t,t+5]}$ is the share of promotions for migrant (native) employees. *Foreign(Domestic)_VC*$_{[t,t+5]}$ is a dummy variable indicating whether a firm is invested by a foreign (domestic) VC. *Foreign(Domestic)_TopVC*$_{[t,t+5]}$ is the logarithm of one plus the number of foreign (domestic) Top VCs, defined by the number of exits. *Foreign(Domestic)_Patent*$_{[t,t+5]}$ is a dummy variable indicating whether a US firm files a overseas (domestic) patent that is eventually granted. The set of control variables include *Manager*, *Experience*, *Serial_Entrepreneur*, and *Number_Founder*. The set of control variables include *Manager*, *Experience*, *Serial_Entrepreneur*, and *Number_Founder*. For all specifications, robust standard errors are clustered at Industry×Year level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively. Table A1 provides detailed variable definitions.

Panel A. Migrant-Native vs. Native: Performance

	First Stage	Second Stage				
	Migrant_Native	*Ln(Emp*$_{t+3}$*)*	*Funded*$_{[t,t+3]}$	*Ln(Raised*$_{[t,t+3]}$*+1)*	*Acq*$_{[t,t+5]}$	*IPO*$_{[t,t+10]}$
	(1)	(2)	(3)	(4)	(5)	(6)
Shift_Share	-0.396***					
	(0.035)					
$\widehat{Migrant\_Native}$		0.333	0.389***	1.182***	0.090*	-0.004
		(0.260)	(0.090)	(0.392)	(0.051)	(0.020)
Controls	Y	Y	Y	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y	Y	Y	Y
University×Degree FE	Y	Y	Y	Y	Y	Y
N	27587	27587	27587	27587	27587	27587
Wald F	129.3					

Panel B. Migrant-Native vs. Native: Foreign Labor, VC, and Patenting

	Second Stage				
	Mig_Emp_Share$_{[t,t+5]}$	*Mig_Promotion*$_{[t,t+5]}$	*Foreign_VC*$_{[t,t+5]}$	*Foreign_TopVC*$_{[t,t+5]}$	*Foreign_Patent*$_{[t,t+5]}$
	(1)	(2)	(3)	(4)	(5)
$\widehat{Migrant\_Native}$	0.375***	0.100*	0.213***	0.091*	0.045*
	(0.055)	(0.058)	(0.079)	(0.048)	(0.025)
Controls	Y	Y	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y	Y	Y
University×Degree FE	Y	Y	Y	Y	Y
N	27587	27587	27587	27587	27587

Panel C. Migrant-Native vs. Migrant: Performance

	First Stage	Second Stage				
	Migrant_Native	*Ln(Emp*$_{t+3}$*)*	*Funded*$_{[t,t+3]}$	*Ln(Raised*$_{[t,t+3]}$*+1)*	*Acq*$_{[t,t+5]}$	*IPO*$_{[t,t+10]}$
	(1)	(2)	(3)	(4)	(5)	(6)
Shift_Share	0.610***					
	(0.051)					
$\widehat{Migrant\_Native}$		0.733**	0.148	1.175**	-0.041	0.070*
		(0.298)	(0.099)	(0.456)	(0.053)	(0.041)
Controls	Y	Y	Y	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y	Y	Y	Y
University×Degree FE	Y	Y	Y	Y	Y	Y
N	6503	6503	6503	6503	6503	6503
Wald F	145.5					

Panel D. Migrant-Native vs. Migrant: Domestic Labor, VC, and Patenting

	Second Stage				
	Native_Emp_Share$_{[t,t+5]}$	*Native_Promotion*$_{[t,t+5]}$	*Domestic_VC*$_{[t,t+5]}$	*Domestic_TopVC*$_{[t,t+5]}$	*Domestic_Patent*$_{[t,t+5]}$
	(1)	(2)	(3)	(4)	(5)
$\widehat{Migrant\_Native}$	0.498***	0.111***	0.119	0.527***	0.086
	(0.078)	(0.042)	(0.102)	(0.164)	(0.062)
Controls	Y	Y	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y	Y	Y
University×Degree FE	Y	Y	Y	Y	Y
N	6503	6503	6503	6503	6503

Table 10. LATE vs. ATE: Same Cohort

This table presents firm-level OLS heterogeneity tests with respect to whether all the founders in a startup graduated from the same university in the same year and obtained the same type of degree. *Same_UDY* is a dummy variable that is equal to one if all the co-founders in a startup are from the same university-degree-year. The set of control variables is the same as that in Table 3. For all specifications, robust standard errors are clustered at Industry×Year level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively. Table A1 provides detailed variable definitions.

Panel A: Native vs. Migrant-Native

	$Ln(Emp_{t+3})$	$Funded_{[t,t+3]}$	$Ln(Raised_{[t,t+3]}+1)$	$Acq_{[t,t+5]}$	$IPO_{[t,t+10]}$
	(1)	(2)	(3)	(4)	(5)
Migrant_Native	0.200***	0.041***	0.167***	0.007	0.005*
	(0.028)	(0.010)	(0.036)	(0.005)	(0.003)
Migrant_Native×Same_UDY	0.151***	0.057***	0.125**	-0.011	0.000
	(0.048)	(0.017)	(0.063)	(0.008)	(0.004)
Same_UDY	-0.110***	-0.034***	-0.074**	-0.010**	0.002
	(0.025)	(0.009)	(0.030)	(0.005)	(0.002)
Controls	Y	Y	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y	Y	Y
N	20428	20428	20428	20428	20428

Panel B: Migrant vs. Migrant-Native

	$Ln(Emp_{t+3})$	$Funded_{[t,t+3]}$	$Ln(Raised_{[t,t+3]}+1)$	$Acq_{[t,t+5]}$	$IPO_{[t,t+10]}$
	(1)	(2)	(3)	(4)	(5)
Migrant_Native	0.057	-0.032	0.086	0.028***	0.000
	(0.055)	(0.022)	(0.086)	(0.011)	(0.006)
Migrant_Native×Same_UDY	0.080	0.108***	0.294**	-0.021	0.009
	(0.082)	(0.032)	(0.116)	(0.014)	(0.008)
Same_UDY	0.010	-0.048**	-0.091	-0.011	0.003
	(0.051)	(0.019)	(0.077)	(0.010)	(0.005)
Controls	Y	Y	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y	Y	Y
N	4872	4872	4872	4872	4872

Appendix

Table A1: Variable Definitions

Panel A. Entrepreneur-Level Variables

Variable	Definition	Source
Migrant	An indicator that is equal to one if entrepreneurs establish startups not in their home country. Home country is defined as the initial country that appears in an individual's LinkedIn profile, either in educational pursuits or job positions.	LinkedIn
Native	An indicator that is equal to one if entrepreneurs who establish startups in their home country.	LinkedIn
Bachelor	An indicator that is equal to one if an entrepreneur's highest degree is Bachelor	LinkedIn
Graduate	An indicator that is equal to one if an entrepreneur's highest degree is Master, MBA, or PhD.	LinkedIn
Male	An indicator that is equal to one if an entrepreneur's gender is male	LinkedIn
Serial_Entrepreneur	An indicator that is equal to one if an entrepreneur established a startup before the current one	LinkedIn; Revelio Lab
Manager	An indicator that is equal to one if an entrepreneur held a managerial position before establish a startup	LinkedIn; Revelio Lab
Experience	The number of years of work experience before establishing a startup	LinkedIn
Exp_Engineer	The number of years of engineering-related work experience before establishing a startup	LinkedIn; Revelio Lab

Panel B. Firm-Level Variables

Variable	Definition	Source
Migrant	An indicator that is equal to one if a startup's founding team has at least one migrant entrepreneur.	LinkedIn
Migrant_Native	An indicator that is equal to one if a startup is founded by both migrant and native entrepreneurs.	LinkedIn

Emp_{t+3}	The number of employees (excluding founders) in three years since startup inception year.	LinkedIn
$\text{Mig\_Emp\_Share}_{[t+5]}$	The share of migrant employees relative to all employees over the first five years since the establishment year.	LinkedIn
$\text{All\_Internal\_Promotion}_{[t,t+5]}$	The share of workers hired within the first five years of a firm's inception who are subsequently promoted in the firm, scaled by the total number of employees. The employee seniority ranking is provided by Revelio Lab.	LinkedIn; Revelio Lab
$\text{Native(Mig)\_Internal\_Promotion}_{[t,t+5]}$	The share of native (migrant) workers hired within the first five years of a firm's inception who are subsequently promoted in the firm, scaled by the total number of native (migrant) workers. The employee seniority ranking is provided by Revelio Lab.	LinkedIn; Revelio Lab
$\text{All\_External\_Promotion}_{[t,t+5]}$	The number of workers hired within the first five years of a firm's inception who are subsequently promoted in other firms, scaled by the total number of employees. The employee seniority ranking is provided by Revelio Lab.	LinkedIn; Revelio Lab
$\text{Native(Mig)\_External\_Promotion}_{[t,t+5]}$	The number of native (migrant) workers hired within the first five years of a firm's inception who are subsequently promoted in other firms, scaled by the total number of native (migrant) workers. The employee seniority ranking is provided by Revelio Lab.	LinkedIn; Revelio Lab
$\text{Raised}_{[t,t+3]}$ (\$MM)	Total amount of funding raised between year t and $t+3$ where t is the startup inception year.	Crunchbase
$\text{Funding}_{[t,t+3]}$	An indicator that is equal to one if a startup gets external financing between year t and $t+3$ where t is the startup inception year.	Crunchbase
$\text{Foreign\_VC}_{[t,t+3]}$	An indicator that is equal to one if a firm receives funding from VC based outside the US between year t and $t+3$ where t is the startup inception year.	Crunchbase
$\text{All\_TopVC\_Deal}_{[t,t+3]}$	The number of top VCs that invest in a firm between year t and $t+3$ where t is the startup inception year. Top VC is defined as VC firms with cumulative number of investments ranked in the top 10 percentiles in a given year.	Crunchbase
$\text{Domestic(Foreign)\_TopVC\_Deal}_{[t,t+3]}$	The number of top VCs based in (outside) the US that invest in a firm between year t and $t+3$ where t is the startup inception year. Top VC is defined as VC firms with cumulative number of investments ranked in the top 10 percentiles in a given year.	Crunchbase

All_TopVC_Exit$_{[t,t+3]}$	The number of top VCs that invest in a firm between year t and $t+3$ where t is the startup inception year. Top VC is defined as VC firms with cumulative number of exits (e.g., IPO or acquisition) ranked in the top 10 percentiles in a given year.	Crunchbase
Domestic(Foreign)_TopVC_Exit$_{[t,t+3]}$	The number of top VCs based in (outside) the US that invest in a firm between year t and $t+3$ where t is the startup inception year. Top VC is defined as VC firms with cumulative number of exits (e.g., IPO or acquisition) ranked in the top 10 percentiles in a given year.	Crunchbase
Acq$_{[t,t+5]}$	An indicator that is equal to one if a startup gets acquired between year t and $t+10$ where t is the startup inception year.	Crunchbase
IPO$_{[t,t+10]}$	An indicator that is equal to one if a startup goes public between year t and $t+10$ where t is the startup inception year.	Crunchbase
US(Foreign)_Patent$_{[t,t+5]}$	The number of granted patents that a startup files in (outside) the US between t and $t+5$, where t is the startup inception year.	Google Patent
Bachelor	An indicator that is equal to one if at least one of the founders in a startup holds Bachelor as the highest degree.	LinkedIn
Graduate	An indicator that is equal to one if at least one of the founders in a startup holds Master, MBA, or PhD as the highest degree.	LinkedIn
Serial_Entrepreneur	An indicator that is equal to one if at least one of the founders in a startup established a startup before the current one	LinkedIn; Revelio Lab
Manager	An indicator that is equal to one if at least one of the founders in a startup held a managerial position before establish a startup	LinkedIn; Revelio Lab
Experience	The maximum number of years of work experience among founders before establishing a startup	LinkedIn

Internet Appendix

IA.1 Crunchbase coverage

In this section, we present summary statistics about the firm coverage in Crunchbase. Crunchbase collects data from two main sources: 1) more than 4,000 global investment firms and 2) active community contributors such as executives, entrepreneurs, and investors.[2] Additionally, Crunchbase employs AI and machine learning algorithms, along with manual validation, to ensure data accuracy. In Figure IA6, we present the number of firms covered in Crunchbase by establishment year as well as the firms' industry and state distribution for firms founded between 2000 and 2020.

Panel A illustrates the number of firms established each year from 2000 to 2020, distinguishing between those that secured external financing by 2023 and those that did not. The total number of firms founded increased steadily from approximately 20,000 in 2000 to around 36,000 in 2014, followed by a decline to about 22,000 in 2020. Moreover, the share of firms receiving external financing has risen over time. Among firms founded in 2000, roughly 10% had secured funding by 2023, whereas for those founded in 2020, the figure reached approximately 28%. Panels B and C present the industry and state distributions of firms. The top 10 industries (health care, professional services, financial services, sales and marketing, real estate, commerce and shopping, information technology, internet services, software, and media and entertainment) account for 60% of all firms. The state distribution is even more concentrated, with the top five states, California (21.5%), New York (9.6%), Texas (8.2%), Florida (7.3%), and Illinois (3.8%), comprising 50% of all firms.

IA.2 Estimating founders' outside option values

This section describes how the value of founders' outside option is calculated. We start with the following OLS regression:

$$Ln(Wage_{i,m,u,d,t,j,\tau}) = \beta_1 Exp_{i,j,\tau} + \lambda_{m,u,d,t} + \gamma_{j,\tau} + \varepsilon_{i,m,u,d,t,j,\tau} \tag{7}$$

, where $\text{Wage}_{i,m,u,d,t,j,\tau}$ is the starting salary of individual i who starts a position in industry j in year τ with an immigration status m and graduates from university u with degree d and enrollment

[2] For more information, please see https://support.crunchbase.com/hc/en-us/articles/360009616013-Where-does-Crunchbase-get-their-data

year t, $\text{Exp}_{i,j,\tau}$ is the number of work experience before the position starting in year τ and industry j, $\lambda_{m,u,d,t}$ is the immigrant-university-degree-enrollment_year fixed effects, and $\gamma_{j,\tau}$ is industry-year fixed effects. The value of outside option is equal to fixed effects $\lambda_{m,u,d,t}$.

The wage data is provided by Revelio Lab. To construct the sample, we first merge US firms in LinkedIn with those in Crunchbase using the company LinkedIn profile URLs to get firm industry classification. The details of merging two datasets are described in Section 2.2, and industry classification based on Crunchbase keywords is described in Section 2.3. This step yields 106,242 unique firms with 3,510,902 employees holding 5,780,289 positions. We then extract the full resume (including education histories) of those 3,510,902 employees to get information required to estimate equation (7). In addition, we restrict the sample to contain positions without job titles containing keywords: "founder" or "co-founder" and positions starting no later than ten years since graduation.

IA.3 Replicating labor findings using only LinkedIn sample

To ensure our findings are not influenced by firm coverage in Crunchbase, we replicate our labor-related analyses using only the LinkedIn database. Since both our labor-related outcome variables and all control variables are derived solely from LinkedIn, the key difference between this replication and our main analyses lies in the sample of firms included.

To construct the sample, we first select the firms with unique identifier that is assigned by Revelio Lab. Since company names are self-reported in LinkedIn, it would be difficult to keep track of a firm without such a unique identifier. We then restrict the sample to firms with non-missing NAICS code provided by Revelio Lab. This restriction allows us to maintain the consistency of the regression specification by including Industry$\times$Est. Year fixed effects. Finally, following the sample construction in our baseline analysis, we restrict firms to have multiple co-founders, have at least one of the co-founders based in the US, and have at least one employee three years after the inception. The final sample consists of 33,331 firms established between 2000 and 2017.

Table IA15 presents replication results for the baseline labor findings in Table 3 and the findings for the native and migrant labor pools in Table 4. The replication yields qualitatively identical and quantitatively similar results, reinforcing the robustness of our main findings on the superior performance of migrant-native startups across different firm coverage.

Figure IA1: Migrant Founder Type

Panel A plots the share of each type of migrant founders (e.g., migrants co-founding startups with natives) within migrant entrepreneurs. In each year, the shares of four types add up to one. *Single_Founder* indicates migrant entrepreneurs who establish startups without co-founding with others. *Migrant_Native* indicates migrant entrepreneurs who co-found startups with native entrepreneurs. *Same_Origin* indicates migrant entrepreneurs who co-found startups with migrant entrepreneurs from the same country of origin. *Mixed_Origin* indicates migrant entrepreneurs who co-found startups with migrant entrepreneurs from the different countries of origin. Panel B plots the trend of the number of migrant-founded startups in the US from 2000 to 2022

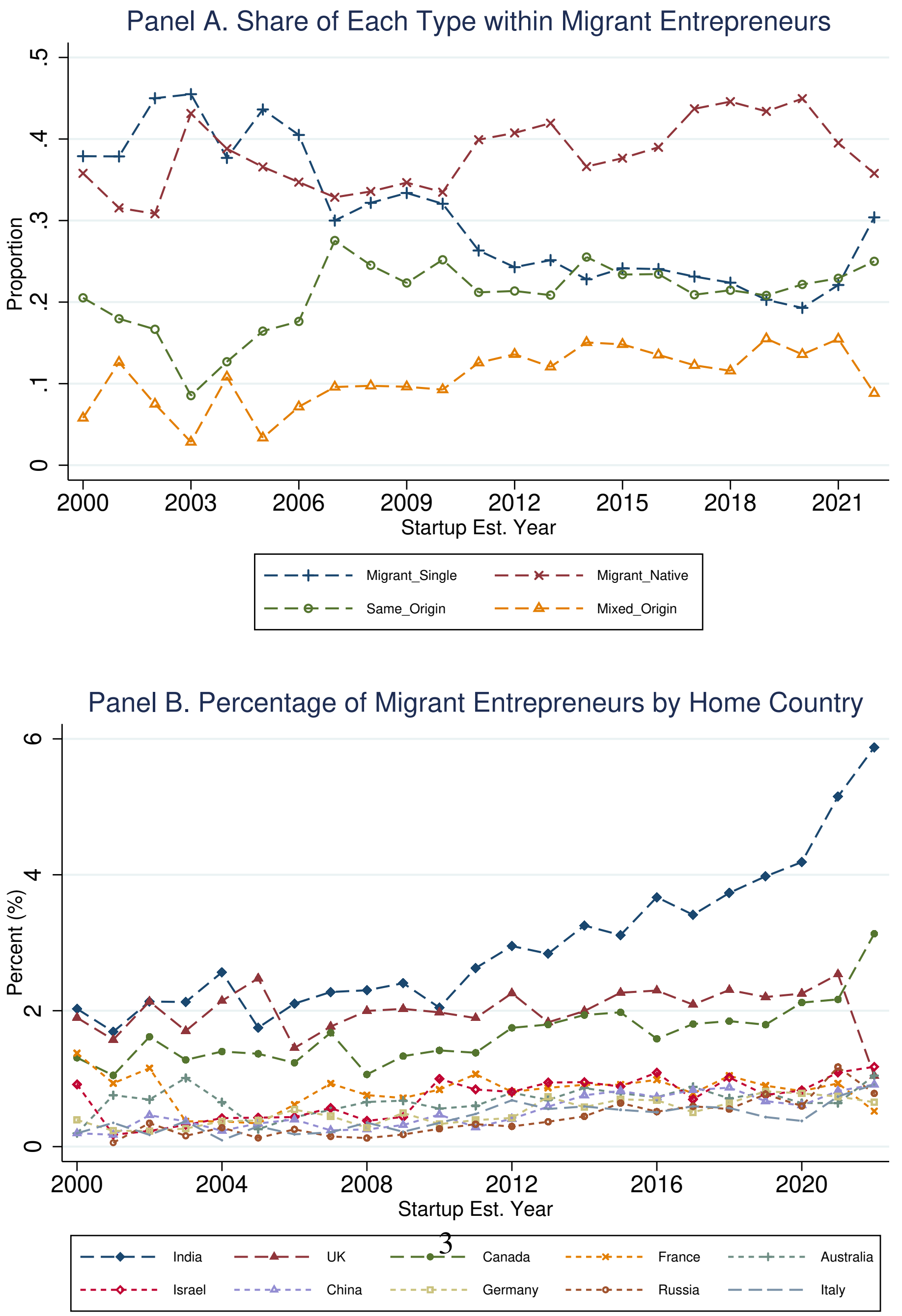

Figure IA2: Top Ten Industries where Migrant Entrepreneurs Establish Startups in the US

This figure shows the top ten industries where migrant entrepreneurs established startups in the US from 2000 to 2022. The top ten industries are selected based on the number of migrant entrepreneurs. The industry classification is based on that of Crunchbase database.

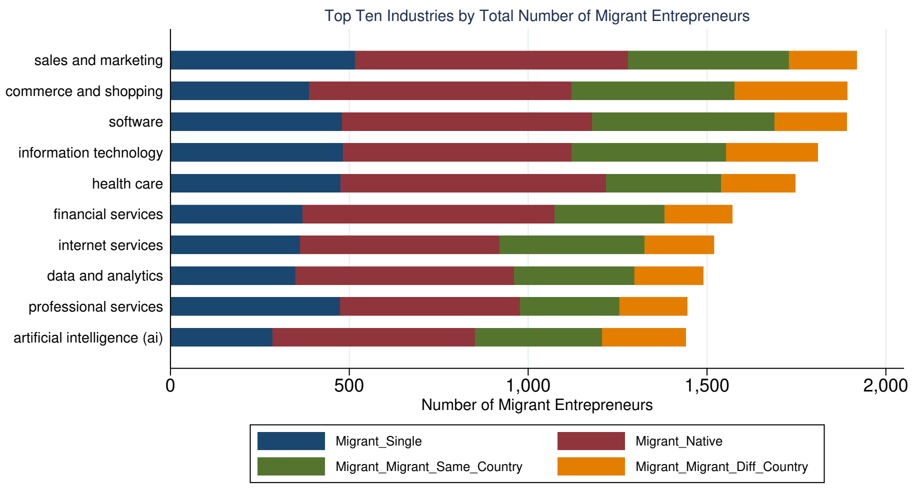

Figure IA3: Skill Composition in Founding Team

This figure displays skill composition in founding team. *Business-Business* indicates that all the founders in a startup with previous working experience in marketing, finance, admin, sales, or operation that are classified by Revelio Labs. *Tech-Tech* indicates that all the founders in a startup with previous working experience in engineer or science that are classified by Revelio Labs. *NativeBusiness-MigTech* indicates that at least one co-founder has business background and at least one co-founder has technology background.

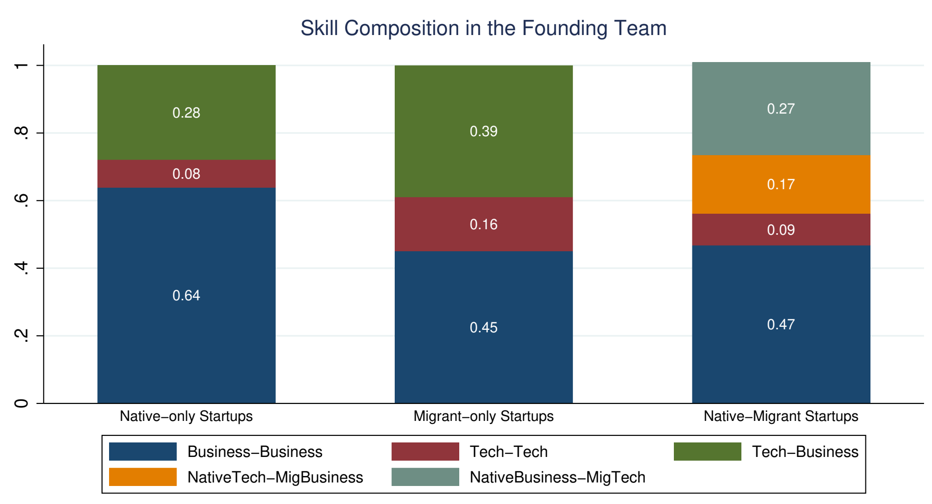

Figure IA4: Ethnicity Composition in Founding Team

This figure shows whether founding team members share the same ethnicity based on two ethnicity classifications. The first one is provided by Revelio Lab and contains five ethnicities: Asia, Black, Hispanic, Native, and White. The second one is based on a machine learning algorithm, ethnicseer, to predict one's ethnicity based on his/her full name. This algorithm has 12 ethnicities: Middle-Eastern, Chinese, English, French, Vietnam, Spanish, Italian, German, Japanese, Russian, Indian, and Korean.

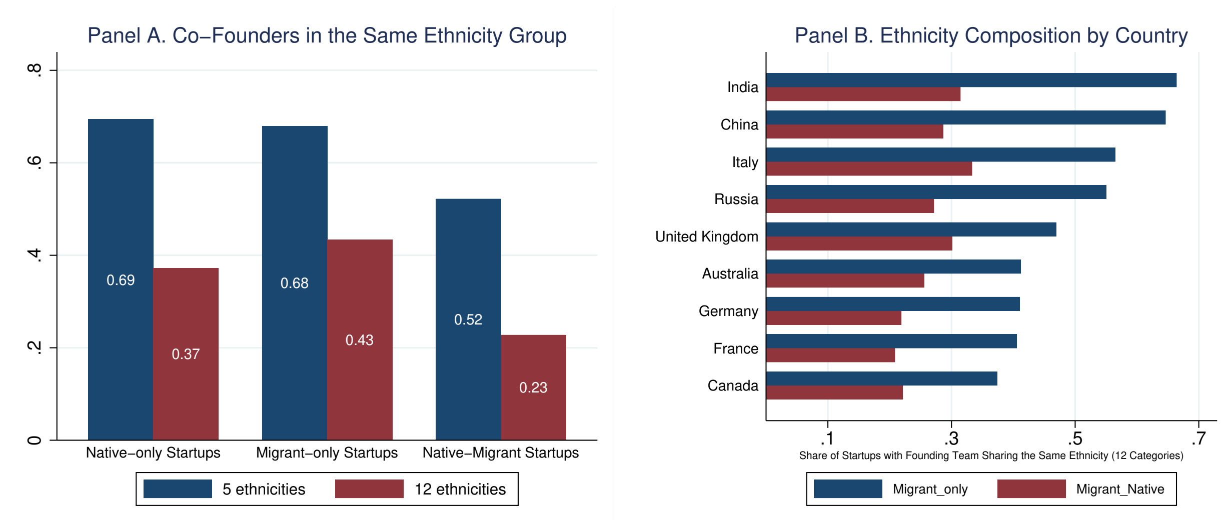

Figure IA5: Binned Scatterplots for the First Stage of 2SLS

This figure plots the binned scatterplots for a visual representation of the first stage results reported in Table 8.

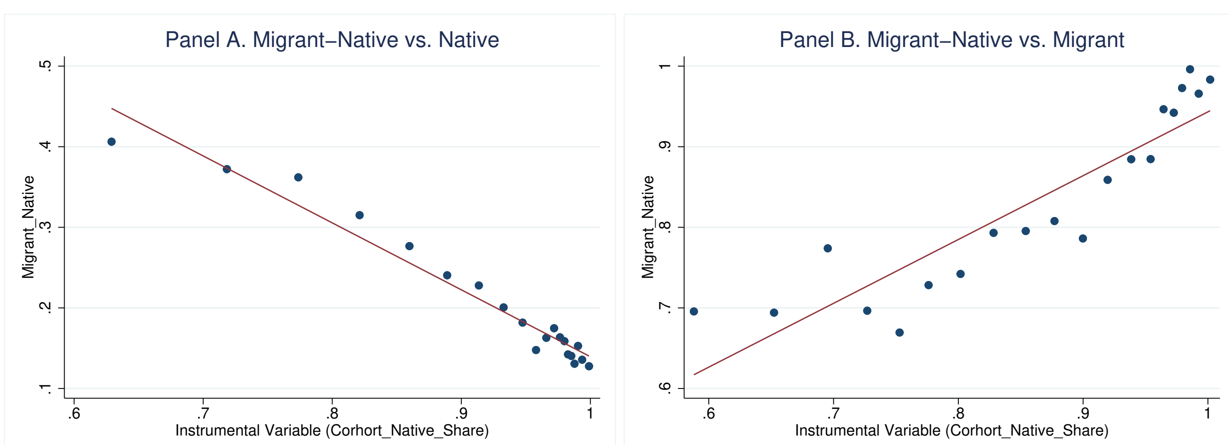

Figure IA6: Firm Coverage in Crunchbase

This figure plots the number of firms covered in Crunchbase by establishment year as well as the firms' industry and state distributions for firms founded between 2000 and 2020.

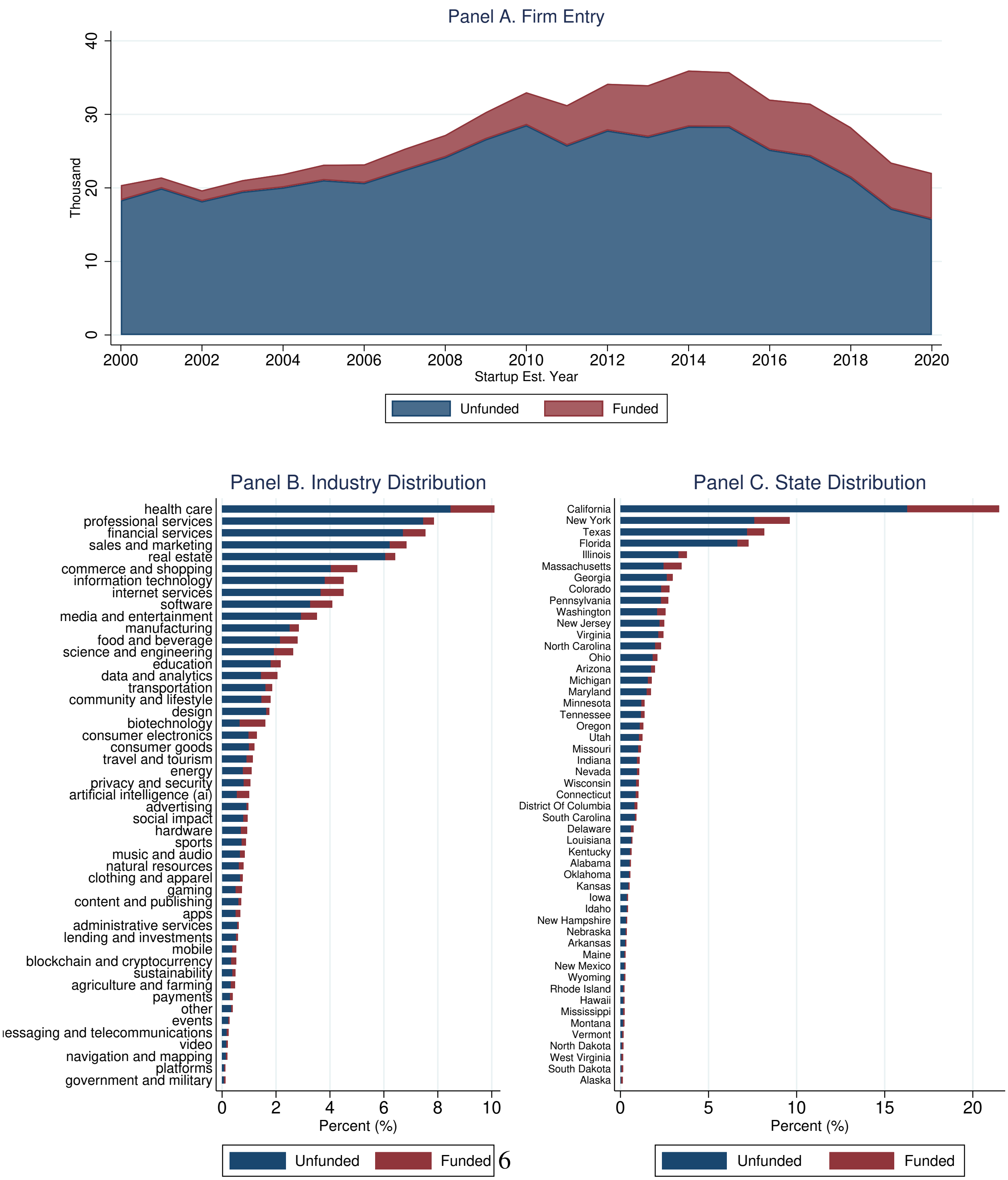

Table IA1. Entrepreneur-Level Summary Statistics: All Entrepreneurs

This table provides the summary statistics at entrepreneurs level. The sample consists of 94,886 entrepreneurs who establish startups with other entrepreneurs between 2000 and 2017 in the US. We compare the characteristics of native entrepreneurs with those of migrant entrepreneurs. Table A1 provides detailed variable definitions.

	N(Migrant)	N(Native)	μ(Migrant)	μ(Native)	Migrant - Native
Bachelor	17538	77348	0.23	0.31	-0.08***
Graduate	17538	77348	0.43	0.26	0.17***
Top10_University	17538	77348	0.04	0.04	-0.01***
Top50_University	17538	77348	0.07	0.06	0.01***
Top100_University	17538	77348	0.04	0.03	0.01***
Male	17538	77348	0.70	0.76	-0.06***
Serial_Entrepreneur	17538	77348	0.40	0.40	0.00
Manager	17538	77348	0.53	0.50	0.03***
Experience	17538	77348	9.82	9.74	0.09
Exp_Engineer	17538	77348	2.91	1.76	1.15***
Exp_Finance	17538	77348	0.55	0.92	-0.37***
Exp_Marketing	17538	77348	1.44	1.72	-0.28***
Exp_Operation	17538	77348	1.12	1.19	-0.07**
Exp_Sales	17538	77348	2.59	2.74	-0.15***
Exp_Scientist	17538	77348	0.85	0.63	0.22***
Observations	94886				

Table IA2. Startup-Level Summary Statistics: All Startups

This table provides the summary statistics at firm level. The sample consists of 66,576 firms established between 2000 and 2017 in the US. Table A1 provides detailed variable definitions.

	N	Mean	Std	P1	P25	P50	P75	P99
Migrant	66576	0.19	0.39	0.00	0.00	0.00	0.00	1.00
Migrant_Native	66576	0.08	0.27	0.00	0.00	0.00	0.00	1.00
Emp_{t+3}	66576	15.23	378.83	1.00	2.00	4.00	10.00	104.00
$Mig\_Emp\_Share_{[t,t+5]}$	66576	0.24	0.31	0.00	0.00	0.10	0.38	1.00
$Raised_{[t,t+3]}$ *($MM)*	66576	18.45	185.92	0.00	0.00	0.00	0.00	378.00
$Funded_{[t,t+3]}$	66576	0.23	0.42	0.00	0.00	0.00	0.00	1.00
$Foreign\_VC_{[t,t+3]}$	66576	0.10	0.30	0.00	0.00	0.00	0.00	1.00
$All\_Top\_VC\_Deal_{[t,t+3]}$	66576	0.92	3.68	0.00	0.00	0.00	0.00	18.00
$Foreign\_Top\_VC\_Deal_{[t,t+3]}$	66576	0.11	0.78	0.00	0.00	0.00	0.00	3.00
$Domestic\_Top\_VC\_Deal_{[t,t+3]}$	66576	0.80	3.32	0.00	0.00	0.00	0.00	16.00
$All\_Top\_VC\_Exit_{[t,t+3]}$	66576	0.46	2.12	0.00	0.00	0.00	0.00	10.00
$Foreign\_Top\_VC\_Exit_{[t,t+3]}$	66576	0.04	0.38	0.00	0.00	0.00	0.00	1.00
$Domestic\_Top\_VC\_Deal_{[t,t+3]}$	66576	0.43	1.98	0.00	0.00	0.00	0.00	9.00
$Acq_{[t,t+5]}$	66576	0.04	0.19	0.00	0.00	0.00	0.00	1.00
$IPO_{[t,t+10]}$	66576	0.01	0.10	0.00	0.00	0.00	0.00	0.00
Number_Founders	66576	1.52	1.17	1.00	1.00	1.00	2.00	5.00
Bachelor	66576	0.36	0.48	0.00	0.00	0.00	1.00	1.00
Graduate	66576	0.35	0.48	0.00	0.00	0.00	1.00	1.00
Serial_Entrepreneur	66576	0.50	0.50	0.00	0.00	1.00	1.00	1.00
Manager	66576	0.60	0.49	0.00	0.00	1.00	1.00	1.00
Experience	66576	11.29	8.38	0.00	5.00	10.00	17.00	33.00
Top10_University	66576	0.06	0.23	0.00	0.00	0.00	0.00	1.00
Top50_University	66576	0.08	0.28	0.00	0.00	0.00	0.00	1.00
Top100_University	66576	0.05	0.21	0.00	0.00	0.00	0.00	1.00
$All\_Patent_{[t,t+5]}$	66576	0.44	9.29	0.00	0.00	0.00	0.00	10.00
$US\_Patent_{[t,t+5]}$	66576	0.31	5.35	0.00	0.00	0.00	0.00	6.00
$Foreign\_Patent_{[t,t+5]}$	66576	0.13	4.32	0.00	0.00	0.00	0.00	2.00
Business_Business	66576	0.73	0.44	0.00	0.00	1.00	1.00	1.00
Tech_Tech	66576	0.16	0.36	0.00	0.00	0.00	0.00	1.00
Tech_Business	66576	0.11	0.31	0.00	0.00	0.00	0.00	1.00

Table IA3. Employee-Level Summary Statistics

This table provides the summary statistics at employee level. The sample consists of 3,520,520 employees who work for the US firms in our sample and start their positions within five years of firms' inception year. We compare the characteristics of native workers with those of migrants. *Marketing*, *Finance*, *Sales*, *Operation*, *Engineer*, and *Science* are indicators that are equal to one if a worker's position falls into the corresponding job category provided by Revelio Lab.

	N(Migrant)	N(Native)	μ(Migrant)	μ(Native)	Migrant - Native
Bachelor	1288041	2232479	0.20	0.33	-0.13***
Graduate	1288041	2232479	0.21	0.18	0.03***
Manager	1288041	2232479	0.18	0.23	-0.05***
Engineer	1288041	2232479	0.39	0.19	0.19***
Scientist	1288041	2232479	0.04	0.09	-0.05***
Finance	1288041	2232479	0.12	0.09	0.03***
Marketing	1288041	2232479	0.14	0.21	-0.07***
Operation	1288041	2232479	0.05	0.05	-0.00***
Sales	1288041	2232479	0.15	0.23	-0.08***
Observations	3520520				

Table IA4. Robustness Checks: OLS Estimates

This table presents a set of robustness tests. The set of control variables is the same as that in Table 3. For all specifications, robust standard errors are clustered at Industry×Year level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively. Table A1 provides detailed variable definitions.

Panel A. Founder-Startup Level with the US University and Degree Fixed Effects

	Ln(Emp$_{t+3}$)		*Funded$_{[t,t+3]}$*		*Ln(Raised$_{[t,t+3]}$+1)*		*Acq$_{[t,t+5]}$*		*IPO$_{[t,t+10]}$*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Migrant	0.132***	0.074	0.100***	0.015	0.210**	-0.087	-0.022***	-0.030***	-0.001	-0.002
	(0.047)	(0.049)	(0.019)	(0.019)	(0.082)	(0.081)	(0.008)	(0.009)	(0.004)	(0.005)
Migrant_Native	0.187***	0.197***	0.012	0.058***	0.255***	0.397***	0.038***	0.040***	0.009*	0.008*
	(0.050)	(0.049)	(0.020)	(0.019)	(0.088)	(0.086)	(0.010)	(0.011)	(0.005)	(0.005)
Serial_Entrepreneur	0.115***	0.099***	0.047***	0.035***	0.177***	0.139***	0.009***	0.007**	0.004**	0.003*
	(0.016)	(0.016)	(0.006)	(0.006)	(0.026)	(0.026)	(0.003)	(0.003)	(0.002)	(0.002)
Manager	0.146***	0.135***	0.024***	0.025***	0.125***	0.134***	0.006*	0.007*	0.005***	0.005***
	(0.017)	(0.018)	(0.006)	(0.006)	(0.026)	(0.026)	(0.003)	(0.003)	(0.002)	(0.002)
Experience	0.001	0.001	-0.000	0.000	0.004	0.004*	0.001***	0.001***	0.000**	0.000**
	(0.002)	(0.001)	(0.000)	(0.000)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Number_Founders	0.054***	0.057***	0.000	0.001	0.013	0.017	-0.000	0.000	0.000	0.000
	(0.014)	(0.013)	(0.003)	(0.003)	(0.015)	(0.014)	(0.001)	(0.001)	(0.000)	(0.000)
Industry × Est. Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
University FE	N	Y	N	Y	N	Y	N	Y	N	Y
Degree FE	N	Y	N	Y	N	Y	N	Y	N	Y
N	32223	31634	32223	31634	32223	31634	32223	31634	32223	31634
Adj. R^2	0.122	0.150	0.133	0.192	0.116	0.166	0.050	0.048	0.071	0.069

Panel B. All Startups with Number of Founders Fixed Effects

	Ln(Emp$_{t+3}$)		*Funded$_{[t,t+3]}$*		*Ln(Raised$_{[t,t+3]}$+1)*		*Acq$_{[t,t+5]}$*		*IPO$_{[t,t+10]}$*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Migrant	0.161***	0.142***	0.051***	0.047***	0.103***	0.050***	-0.004*	-0.009***	0.002	-0.000
	(0.014)	(0.016)	(0.005)	(0.006)	(0.016)	(0.018)	(0.002)	(0.002)	(0.001)	(0.001)
Migrant_Native		0.051**		0.010		0.148***		0.015***		0.005*
		(0.021)		(0.010)		(0.032)		(0.004)		(0.003)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
No. Founder FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	66549	66549	66549	66549	66549	66549	66549	66549	66549	66549
Adj. R^2	0.078	0.078	0.166	0.166	0.176	0.177	0.021	0.021	0.043	0.043

Panel C. Sample Conditional on Getting Funded within Three Years

	Ln(Emp$_{t+3}$)		*Ln(Raised$_{[t,t+3]}$+1)*		*Acq$_{[t,t+5]}$*		*IPO$_{[t,t+10]}$*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Migrant	0.119***	-0.013	0.151***	-0.123*	-0.009	-0.037***	0.002	-0.005
	(0.029)	(0.043)	(0.045)	(0.072)	(0.008)	(0.010)	(0.005)	(0.006)
Migrant_Native		0.187***		0.389***		0.038***		0.010*
		(0.041)		(0.073)		(0.011)		(0.006)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	7192	7192	7192	7192	7192	7192	7192	7192
Adj. R^2	0.048	0.050	0.116	0.120	0.014	0.015	0.092	0.092

Panel D. State×Est. Year Fixed Effects

	Ln(Emp$_{t+3}$)	*Funded$_{[t,t+3]}$*	*Ln(Raised$_{[t,t+3]}$+1)*	*Acq$_{[t,t+5]}$*	*IPO$_{[t,t+10]}$*
	(1)	(2)	(3)	(4)	(5)
Migrant	0.106***	0.054***	0.050	-0.017*	-0.002
	(0.034)	(0.014)	(0.056)	(0.009)	(0.003)
Migrant_Native	0.075**	-0.003	0.116**	0.020**	0.007**
	(0.036)	(0.015)	(0.057)	(0.010)	(0.003)
Controls	Y	Y	Y	Y	Y
Industry × Est.Year FE	Y	Y	Y	Y	Y
State × Est.Year FE	Y	Y	Y	Y	Y
N	21132	21132	21132	21132	21132
Adj. R^2	0.069	0.178	0.166	0.049	0.047

Panel E. Poisson Regression for *Raised*$_{[t,t+3]}$

	Raised$_{[t,t+3]}$	
	(1)	(2)
Migrant	0.327***	0.099
	(0.102)	(0.133)
Migrant_Native		0.300**
		(0.137)
Industry × Est. Year FE	Y	Y
N	22115	22115
Pseudo R^2	0.274	0.275

Table IA5. Startup Failure

This table examines whether migrant-only and migrant-native, relative native-only, startups are less likely to fail within five years of the establishment. Startup failure measure is based on the number of employees in the fifth year since the startup inception. The set of control variables is the same as that in Table 3. For all specifications, robust standard errors are clustered at Industry$\times$Year level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively. Table A1 provides detailed variable definitions.

	$Emp_{t+5} = 0$	$Emp_{t+5} \leq 3$	$Emp_{t+5} \leq 5$
	(1)	(2)	(3)
Migrant	-0.030***	-0.050***	-0.058***
	(0.008)	(0.010)	(0.011)
Migrant_Native	0.003	-0.005	-0.012
	(0.008)	(0.010)	(0.011)
Controls	Y	Y	Y
Industry $\times$ Est. Year FE	Y	Y	Y
N	22912	22912	22912
Adj. R^2	0.010	0.029	0.036

Table IA6. Robustness Checks: Potential Measurement Error in Identifying Immigrants

This table examines whether our baseline results are affected by measurement error in identifying immigrant. Panel A restricts the sample to startups with all of the co-founders who list their undergraduate degrees on LinkedIn. Panel B repeats the baseline OLS analyses excluding native-migrant startups with founders from the top-10 countries in terms of the share of immigrants with US bachelor's degrees. These countries are: Saudi Arabia, Kuwait, Malaysia, Singapore, Sweden, Indonesia, Nepal, Norway, China, and Bahamas, with Saudi Arabia having the highest share at 33%, and the Bahamas the lowest at 4.5%. For all specifications, robust standard errors are clustered at Industry×Year level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively. Table A1 provides detailed variable definitions.

Panel A. Conditional on Individuals with Undergraduate Degrees Listed on LinkedIn

	$Ln(Emp_{t+3})$	$Funded_{[t,t+3]}$	$Ln(Raised_{[t,t+3]}+1)$	$Acq_{[t,t+5]}$	$IPO_{[t,t+10]}$
	(1)	(2)	(3)	(4)	(5)
Migrant	0.121***	0.049***	0.066	-0.021***	-0.000
	(0.041)	(0.018)	(0.066)	(0.008)	(0.003)
Migrant_Native	0.095**	0.025	0.214***	0.031***	0.007*
	(0.045)	(0.021)	(0.074)	(0.009)	(0.004)
Controls	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y
N	11866	11866	11866	11866	11866
Adj. R^2	0.020	0.099	0.073	0.012	0.063

Panel B. Remove Potential False Positive Native-Migrant Startups

	$Ln(Emp_{t+3})$	$Funded_{[t,t+3]}$	$Ln(Raised_{[t,t+3]}+1)$	$Acq_{[t,t+5]}$	$IPO_{[t,t+10]}$
	(1)	(2)	(3)	(4)	(5)
Migrant	0.152***	0.045***	0.001	-0.024***	-0.001
	(0.029)	(0.012)	(0.045)	(0.007)	(0.002)
Migrant_Native	0.072**	0.008	0.194***	0.028***	0.006**
	(0.030)	(0.013)	(0.049)	(0.008)	(0.003)
Industry × Est. Year FE	Y	Y	Y	Y	Y
University×Degree FE	N	N	N	N	N
N	22618	22618	22618	22618	22618
Adj. R^2	0.066	0.152	0.143	0.047	0.049

Table IA7. Country of Origin

This table examines whether the effects of migrant co-founders on hiring migrant employees and attracting foreign top VCs, documented in Table 4 and Table 5, are concentrated in migrant workers and foreign VCs with the same country of origins as those of migrant founders. In Panel A, we report OLS estimates at individual level. The sample is restricted to migrant employees. *Same_Origin* is an indicator that is equal to one if an migrant worker's country of origin is same as one of the migrant co-founders'. In Panel B, we report OLS estimates with each dependent variable being the share of external promotions for migrant employees from a specific country. We select ten countries that are ranked in the top ten based on the share of migrant employees. In Panel C, we report Poisson estimates with each dependent variable representing the number of top VCs defined by the number of deals from a specific country that invest US startups within the first five years of inception. We select ten countries that are ranked in the top ten based on the number of top VCs that invest in the US startups. The set of control variables is the same as that in Table 3. For all specifications, robust standard errors are clustered at Industry×Year level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively. Table A1 provides detailed variable definitions.

Panel A. Migrant Employees at Individual Level

	External Promotion (Mean = 0.148)	*Internal Promotion (Mean = 0.154)*
	(1)	(2)
Migrant	0.004	0.005
	(0.003)	(0.003)
Migrant×Same_Origin	0.006**	0.009***
	(0.003)	(0.003)
Migrant_Native	-0.003	0.005
	(0.005)	(0.006)
Migrant_Native×Same_Origin	-0.009	-0.005
	(0.008)	(0.009)
Controls	Y	Y
Industry×Est. Year FE	Y	Y
N	909475	909475
Adj. R^2	0.006	0.013

Panel B. Migrant External Promotions by Country

	Share of External Promotion$_{[t,t+5]}$									
	India	*UK*	*France*	*Canada*	*Netherlands*	*China*	*Brazil*	*Australia*	*Philippines*	*Spain*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Migrant	-0.006***	-0.001*	-0.000	-0.002***	0.000	-0.001***	0.000	-0.000	-0.001***	0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Migrant_Native	0.007***	0.002**	0.001***	0.002***	0.000	0.001***	0.000**	0.001***	0.001***	-0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Migrant_India	0.104***									
	(0.006)									
Migrant_Native_India	-0.030***									
	(0.006)									
Migrant_UK		0.034***								
		(0.004)								
Migrant_Native_UK		-0.012***								
		(0.005)								
Migrant_France			0.039***							
			(0.004)							
Migrant_Native_France			-0.016***							
			(0.005)							
Migrant_Canada				0.041***						
				(0.005)						
Migrant_Native_Canada				-0.024***						
				(0.006)						
Migrant_Netherlands					0.017***					
					(0.003)					
Migrant_Native_Netherlands					-0.007*					
					(0.004)					
Migrant_China						0.043***				
						(0.005)				
Migrant_Native_China						-0.011*				
						(0.006)				
Migrant_Brazil							0.047***			
							(0.005)			
Migrant_Native_Brazil							-0.016**			
							(0.007)			
Migrant_Australia								0.018***		
								(0.003)		
Migrant_Native_Australia								-0.008***		
								(0.003)		
Migrant_Philippines									0.006*	
									(0.004)	
Migrant_Native_Philippines									0.001	
									(0.004)	
Migrant_Spain										0.026***
										(0.003)
Migrant_Native_Spain										-0.011**
										(0.004)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	22912	22912	22912	22912	22912	22912	22912	22912	22912	22912
Adj. R^2	0.133	0.040	0.100	0.025	0.069	0.069	0.117	0.042	0.007	0.089

Panel C. Foreign Top VCs by Country

	Number of Top VCs by Deals$_{[t,t+5]}$									
	UK	*China*	*Japan*	*Canada*	*France*	*Germany*	*SouthKorea*	*India*	*Singapore*	*Israel*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Migrant	0.748***	0.223	-0.051	-0.761**	0.252	0.818***	0.398	1.010*	0.771*	-0.471
	(0.174)	(0.405)	(0.280)	(0.357)	(0.261)	(0.231)	(0.527)	(0.596)	(0.428)	(0.539)
Migrant_Native	-0.067	0.277	0.872***	1.111***	0.198	-0.154	0.531	-0.222	0.180	1.469***
	(0.247)	(0.411)	(0.314)	(0.427)	(0.318)	(0.229)	(0.477)	(0.790)	(0.405)	(0.570)
Migrant_UK	1.979***									
	(0.356)									
Migrant_Native_UK	-0.777*									
	(0.433)									
Migrant_China		3.067***								
		(0.459)								
Migrant_Native_China		-0.335								
		(0.543)								
Migrant_Japan			5.733***							
			(0.608)							
Migrant_Native_Japan			-2.604***							
			(0.727)							
Migrant_Canada				4.136***						
				(0.425)						
Migrant_Native_Canada				-2.174***						
				(0.526)						
Migrant_France					3.723***					
					(0.302)					
Migrant_Native_France					-0.565					
					(0.425)					
Migrant_Germany						2.980***				
						(0.377)				
Migrant_Native_Germany						-0.398				
						(0.571)				
Migrant_SouthKorea							5.453***			
							(0.727)			
Migrant_Native_SouthKorea							-0.395			
							(0.883)			
Migrant_India								3.769***		
								(0.516)		
Migrant_Native_India								-0.877		
								(1.029)		
Migrant_Singapore									1.777*	
									(0.945)	
Migrant_Native_Singapore									-1.496	
									(1.253)	
Migrant_Israel										5.836***
										(0.570)
Migrant_Native_Israel										-2.098***
										(0.681)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	14399	9634	9694	10312	11168	11203	5441	5513	9826	8920
Pseudo R^2	0.219	0.304	0.242	0.269	0.330	0.248	0.419	0.457	0.157	0.533

Table IA8. Heterogeneity Test: Skill Complementarity

This table presents tests examining whether there is a difference between migrant and native founders in the type of position prior to founding startups as well as whether the composition of the founding team in terms of skill diversity (i.e., technology vs. business) contributes to the superior performance of native-migrant startups. A founder's skill is classified into seven categories: marketing, finance, administration, sales, operations, engineering, and science, provided by Revelio Labs. These are then grouped into two broad categories: business-related skills (marketing, finance, administration, sales, and operations) and tech-related skills (engineering and science). For all specifications, robust standard errors are clustered at Industry×Year level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively. Table A1 provides detailed variable definitions.

Panel A. Founder Prior Work Experience

	Engineer_Exp	*Scientist_Exp*	*Admin_Exp*	*Finance_Exp*	*Marketing_Exp*	*Operations_Exp*	*Sales_Exp*
	(1)	(2)	(3)	(4)	(5)	(6)	
Migrant	0.398**	0.310***	0.161**	-0.143**	-0.243**	-0.121	-0.074
	(0.155)	(0.114)	(0.081)	(0.069)	(0.116)	(0.102)	(0.185)
Serial_Entrepreneur	0.069	-0.196***	-0.150***	-0.296***	0.081	0.126**	1.603***
	(0.078)	(0.055)	(0.044)	(0.042)	(0.069)	(0.061)	(0.103)
Manager	-0.132	-0.085*	-0.094*	0.125***	0.067	0.256***	0.317***
	(0.087)	(0.049)	(0.055)	(0.046)	(0.077)	(0.061)	(0.093)
Experience	0.159***	0.066***	0.069***	0.068***	0.113***	0.139***	0.297***
	(0.009)	(0.007)	(0.005)	(0.007)	(0.009)	(0.007)	(0.011)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y	Y	Y
University FE	Y	Y	Y	Y	Y	Y	Y
Degree FE	Y	Y	Y	Y	Y	Y	Y
N	24283	24283	24283	24283	24283	24283	24283
Adj. R^2	0.368	0.398	0.278	0.412	0.379	0.277	0.370

Panel B. Heterogeneity Test

	Ln(Emp$_{t+3}$)		*Funded$_{[t,t+3]}$*		*Ln(Raised$_{[t,t+3]}$+1)*		*Acq$_{[t,t+5]}$*		*IPO$_{[t,t+10]}$*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Migrant	0.151***	0.118**	0.054***	0.051**	0.032	0.011	-0.015***	-0.019	0.000	0.008
	(0.034)	(0.056)	(0.013)	(0.024)	(0.049)	(0.096)	(0.005)	(0.012)	(0.003)	(0.006)
Migrant_Native	0.076**	0.056	0.011	-0.002	0.132**	0.150*	0.017**	0.019**	0.004	0.003
	(0.037)	(0.051)	(0.015)	(0.020)	(0.060)	(0.085)	(0.007)	(0.009)	(0.003)	(0.005)
Migrant×Tech_Bus	-0.000		-0.025		-0.058		-0.020**		0.001	
	(0.053)		(0.021)		(0.085)		(0.009)		(0.005)	
Migrant_Native×Tech_Bus	0.007		-0.001		0.145		0.022*		0.002	
	(0.061)		(0.023)		(0.102)		(0.012)		(0.006)	
Migrant_Native×NativeBus		0.065		0.009		0.047		0.004		-0.007
		(0.053)		(0.022)		(0.099)		(0.013)		(0.007)
NativeBus		-0.037		0.007		0.005		0.005		0.009
		(0.057)		(0.024)		(0.096)		(0.012)		(0.007)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	22912	22912	22912	22912	22912	22912	22912	22912	22912	22912
Adj. R^2	0.066	0.066	0.153	0.153	0.144	0.144	0.020	0.020	0.052	0.052

Table IA9. Heterogeneity Test: Ethnic Ties

This table presents tests examining whether the founding team of migrant-founded startups are more likely to share the same ethnicity and whether same ethnic tie contributes to the superior performance of startups. Ethnicity is based on two ethnicity classifications. The first one is provided by Revelio Lab and contains five ethnicities: Asia, Black, Hispanic, Native, and White. The second one is based on a machine learning algorithm, ethnicseer, to predict oneâs ethnicity based on his/her full name. This algorithm has 12 ethnicities: Middle-Eastern, Chinese, English, French, Vietnam, Spanish, Italian, German, Japanese, Russian, Indian, and Korean. Panel B uses the classification of 12 ethnicities. For all specifications, robust standard errors are clustered at Industry×Year level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively. Table A1 provides detailed variable definitions.

Panel A. Founding Team Ethnicity

	Same Race (5 categories)	*Same Race (12 categories)*
	(1)	(2)
Migrant	0.011	0.092***
	(0.011)	(0.011)
Migrant_Native	-0.145***	-0.180***
	(0.013)	(0.012)
Industry × Est. Year FE	Y	Y
N	22912	22912
Adj. R^2	0.062	0.064

Panel B. Heterogeneity Test

	$Ln(Emp_{t+3})$	$Funded_{[t,t+3]}$	$Ln(Raised_{[t,t+3]}+1)$	$Acq_{[t,t+5]}$	$IPO_{[t,t+10]}$
	(1)	(2)	(3)	(4)	(5)
Migrant	0.104***	0.054***	0.019	-0.026***	-0.001
	(0.038)	(0.015)	(0.057)	(0.006)	(0.003)
Migrant_Native	0.094**	-0.008	0.169***	0.025***	0.006
	(0.040)	(0.016)	(0.059)	(0.007)	(0.004)
Migrant×Same_Ethnicity	0.138**	-0.007	0.023	0.011	0.003
	(0.054)	(0.022)	(0.070)	(0.009)	(0.004)
Migrant_Native×Same_Ethnicity	-0.063	0.019	-0.064	0.002	-0.005
	(0.068)	(0.024)	(0.091)	(0.012)	(0.005)
Same_Ethnicity	-0.154***	-0.066***	-0.235***	-0.013***	-0.003*
	(0.021)	(0.007)	(0.028)	(0.003)	(0.002)
Industry × Est. Year FE	Y	Y	Y	Y	Y
N	22912	22912	22912	22912	22912
Adj. R^2	0.069	0.157	0.148	0.020	0.052

Table IA10. 2SLS: Alternative Promotion and Top VC Measures

This table presents 2SLS results at founder-startup level with the instrumental variable *Cohort_Native_Share*. The sample in Panels A contains the startups with at least one native co-founder, and the sample in Panels B include startups with at least one migrant co-founders. For all specifications, robust standard errors are clustered at Industry×Year level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively. Table A1 provides detailed variable definitions.

Native-Migrant vs. Native

	External Promotion	Internal Promotion		TopVC_Exit	TopVC_Deal	
	$All_{[t,t+5]}$	$All_{[t,t+5]}$	$Migrant_{[t,t+5]}$	$All_{[t,t+3]}$	$All_{[t,t+3]}$	$Foreign_{[t,t+5]}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{Migrant\_Native}$	0.042**	0.008	0.017	0.598***	0.945***	0.292***
	(0.020)	(0.027)	(0.047)	(0.133)	(0.168)	(0.070)
Controls	Y	Y	Y	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y	Y	Y	Y
University×Degree FE	Y	Y	Y	Y	Y	Y
N	27601	27601	27601	27601	27601	27601

Native-Migrant vs. Migrant

	External Promotion	Internal Promotion		TopVC_Exit	TopVC_Deal	
	$All_{[t,t+5]}$	$All_{[t,t+5]}$	$Native_{[t,t+5]}$	$All_{[t,t+3]}$	$All_{[t,t+3]}$	$Domestic_{[t,t+5]}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathrm{f}_{m}ig_{n}ative$	-0.012	0.036	0.091**	0.323*	0.233	0.340
	(0.022)	(0.032)	(0.036)	(0.192)	(0.241)	(0.233)
Controls	Y	Y	Y	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y	Y	Y	Y
University×Degree FE	Y	Y	Y	Y	Y	Y
N	6525	6525	6525	6525	6525	6525

Table IA11. Instrumental Variable and Local Economic Condition

This table examines whether local economic condition at state-year level is associated with the average value of instrumental variable in the same state-year. *Average_Corhort_Native_Share* is the average value of the IV for universities in a state-year. For measures of local economic condition, we use state-level GDP, the amount of VC financing, new job creation, new firm entry, and firm exit. We then calculate the geometric mean of annual growth for those measures over the past three years. The data source of VC financing is Crunchbase, and the data source of firm entry and exit are from the US Census. For all specifications, robust standard errors are clustered at State level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

	$GDP\_Growth_{[t-3,t]}$	$VC\_Financing\_Growth_{[t-3,t]}$	$Job\_Creation\_Growth_{[t-3,t]}$	$Entry\_Growth_{[t-3,t]}$	$Exit\_Growth_{[t-3,t]}$
	(1)	(2)	(3)	(4)	(5)
Average_Corhort_Native_Share	-0.023	1.431	-0.016	0.046	0.021
	(0.028)	(1.226)	(0.041)	(0.033)	(0.029)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
N	886	886	886	886	886
Adj. R^2	0.424	0.052	0.674	0.749	0.661

Table IA12. Placebo Tests: Instrumental Variable

This table presents placebo tests to examine whether the instrumental variable is associated with startup performance for native-only startups and migrant-only startups. The set of control variables is the same as that in Table 8. For all specifications, robust standard errors are clustered at Industry×Year level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively. Table A1 provides detailed variable definitions.

	$Ln(Emp_{t+3})$	$Funded_{[t,t+3]}$	$Ln(Raised_{[t,t+3]}+1)$	$Acq_{[t,t+5]}$	$IPO_{[t,t+10]}$
	(1)	(2)	(3)	(4)	(5)
Cohort_Native_Share	-0.022	-0.049	-0.066	0.020	0.001
	(0.085)	(0.033)	(0.144)	(0.021)	(0.009)
Controls	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y
University FE	Y	Y	Y	Y	Y
Degree FE	Y	Y	Y	Y	Y
N	23424	23424	23424	23424	23424
Adj. R^2	0.148	0.210	0.201	0.041	0.071

Table IA13. Founders' Outside Option

This table investigates whether migrant founders, relative to native founders enrolled in the same university degree program during the same enrollment year, exhibit lower-value outside options. This table also shows how firm-level baseline results (Table 3) change once the value of founders' outside options is controlled. The details of calculating the value of outside option is described in Section IA.2 in the Internet Appendix. *Firm_Outside_Option* is the average value of founders' outside options within a startup. The set of control variables is the same as that in Table 3. For all specifications, robust standard errors are clustered at Industry×Year level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively. Table A1 provides detailed variable definitions.

	Outside_Option	*Ln(Emp$_{t+3}$)*	*Funded$_{[t,t+3]}$*	*Ln(Raised$_{[t,t+3]}$+1)*	*Acq$_{[t,t+5]}$*	*IPO$_{[t,t+10]}$*
	(1)	(2)	(3)	(4)	(5)	(6)
Migrant	-0.174***	0.116***	0.034**	0.129**	-0.002	-0.005
	(0.004)	(0.034)	(0.014)	(0.056)	(0.007)	(0.004)
Migrant_Native	-0.001	0.177***	0.063***	0.239***	0.008	0.007**
	(0.002)	(0.031)	(0.011)	(0.045)	(0.006)	(0.003)
Firm_Outside_Option		0.425***	0.248***	1.049***	0.036***	0.008
		(0.068)	(0.026)	(0.110)	(0.012)	(0.007)
University × Degree × Enroll. Year FE	Y	N	N	N	N	N
Industry × Est. Year FE	Y	Y	Y	Y	Y	Y
N	26333	17382	17382	17382	17382	17382
Adj. R^2	0.856	0.070	0.154	0.150	0.016	0.064

Table IA14. Share of Native Students and Extensive Margin

This table examines whether the share of native students leads to more graduates who co-found startups after they graduate. The unit of analysis is university-degree-year, in which the year is enrollment year. In columns (1) to (4), we look into four types of founders: 1) any co-founders, 2) migrant founders who co-found with natives, 3) migrants who co-found with migrants, and 4) natives who co-found with natives. The numbers of co-founders in columns (1) to (4) are scaled by total number of graduates. In column (5), we look into the number of migrants who co-found with anyone, scaled by the number of migrant graduates. In column (6), we look into natives who co-found with anyone, scaled by the number of native graduates. For all specifications, robust standard errors are clustered at University×Degree level and are reported in parentheses. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

	Scaled by All				Scaled by Migrant (Native)	
	Total	*Mig-Native*	*Mig-only*	*Native-only*	*Mig-Founded*	*Native-Founded*
	(1)	(2)	(3)	(4)	(5)	(6)
Share of Native Students	-0.0005	-0.0029*	-0.0024***	0.0048*	-0.0020	-0.0052
	(0.003)	(0.002)	(0.001)	(0.003)	(0.008)	(0.005)
University×Degree FE	Y	Y	Y	Y	Y	Y
Enrollment Year FE	Y	Y	Y	Y	Y	Y
N	23513	23513	23513	23513	23513	23513
Adj. R^2	0.453	0.256	0.175	0.383	0.109	0.411

Table IA15. Replicating Labor-Related Findings Using the LinkedIn Sample

This table presents results that replicate our labor-related baseline results in Table 3 and the results about native and immigrant labor pool in Table 4 with only LinkedIn database. The set of control variables is the same as that in Table 3. For all specifications, robust standard errors are clustered at Industry×Year level and are reported in parentheses. Industry is defined as three-digit NAICS code. *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively. Table A1 provides detailed variable definitions.

			Number of External Promotions			Number of Internal Promotions		
	Ln(Emp$_{t+3}$)	*Mig_Emp_Share$_{[t,t+5]}$*	*All$_{[t,t+5]}$*	*Migrant$_{[t,t+5]}$*	*Native$_{[t,t+5]}$*	*All$_{[t,t+5]}$*	*Migrant$_{[t,t+5]}$*	*Native$_{[t,t+5]}$*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Migrant	0.354***	0.446***	0.780***	1.968***	-0.557***	0.844***	1.968***	-0.557***
	(0.030)	(0.006)	(0.203)	(0.215)	(0.134)	(0.159)	(0.215)	(0.134)
Migrant_Native	0.087***	-0.208***	0.372*	0.204	0.954***	0.378**	0.204	0.954***
	(0.034)	(0.007)	(0.211)	(0.212)	(0.145)	(0.171)	(0.212)	(0.145)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	33331	33331	33293	33193	33302	33327	33193	33302
Adj. R^2	0.124	0.312						
Pseudo R^2			0.440	0.519	0.545	0.500	0.519	0.545