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 entrepreneur teams. Using a unique dataset linking 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. To establish causality, we employ 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.

†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 show that approximately one quarter of new employer businesses in the United States are started by immigrants (**??**). Bernstein et al. (2022b) 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 K. M. 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 (**?**). 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. Over this period, the origin countries with the most migrant entrepreneurs are, in ranked 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 27.4% more migrant employees than native-only startups, while hiring slightly less migrant-workers than migrant-only startups. Native-migrant startups also recruit more technical employees and are more likely to hire workers with graduate degrees than native-only firms. Using internal 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. Heterogeneity analysis further reveals that startup performance is higher across all of our measures (employment growth, funding, acquisition) in industries and states with a high share of employees from the migrant founder's home country.

Turning to capital access, startups founded by native-migrant teams are 8.6% 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 access capital from higher quality VC funds than 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. Heterogeneity analysis reveals the startup performance of native-migrant startups across all measures is higher in those industries where a larger share of the financing comes from investors in the migrant founder's home country.

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 out-

come 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. Finally, in line with our previous heterogeneity results, we show that startup performance by migrant-founded firsts is higher in industries with high patenting activity in the migrant founder's home country.

The causal interpretation of these facts 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, 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 across multiple specifications and with various cross combinations of university, degree, and enrollment year 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. Relative to native-only startups, native-migrant startups are approximately 50% larger in terms of employment size three years following inception. Native-migrant startups are 24 percent 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 these regressions being quite under-powered.

Our two-stage least squares (2SLS) results also provide supporting evidence for the underlying mechanisms. Native-migrant teams are more likely to hire migrant workers and are more likely to access foreign VC capital. The results also indicate that native-migrant teams are more likely to file a foreign patent, although the result is not statistically, again likely due to this regression being under-powered. Overall, these results provide additional evidence that the outperformance of native-migrant startups can be attributed to superior labor market access, capital market access, and product market access.

2 Literature Review

Immigrant entrepreneurship plays a critical role in driving innovation and economic growth, with significant contributions documented across various sectors. W. R. Kerr (2013) and S. P. Kerr and W. R. Kerr (2016) explore the growing trend of immigrant-founded startups, noting their substantial impact on the U.S. economy. Fairlie and Lofstrom (2015) provide a comprehensive review, emphasizing how immigrants contribute disproportionately to business creation and innovation. Azoulay et al. (2022) utilize U.S. administrative data to demonstrate that immigrant entrepreneurs are pivotal in job creation, often through fast-growing startups. Furthermore, Conti and Guzman (2023) offer a comparative analysis of Israeli startups in the U.S., finding that these ventures leverage the U.S.'s advantages in financing and market size to scale effectively. Balachandran and Hernandez (2021) discuss the critical role of venture capital networks that are established through migrant ties, which enable VCs to secure funding and expand their projects internationally. Nanda and Khanna (2010) highlight the importance of diaspora networks, which provide essential resources and facilitate market access for immigrant entrepreneurs.

Immigrant high-skilled workers are key drivers of technological advancement in the U.S. economy. W. R. Kerr (2008) analyze the ethnic composition of U.S. investors, demonstrating how ethnic networks influence innovation outcomes. W. R. Kerr and Lincoln (2010) show how H-1B visas increase the productivity of Asian immigrants without negatively affecting native workers. Hunt

and Gauthier-Loiselle (2010) and Hunt (2011) reveal that immigrants in STEM fields, particularly those entering through student visas, patent at higher rates and perform better in terms of wages and innovation outputs. Further, S. P. Kerr et al. (2016) and Beerli et al. (2021) underscore the role of global talent in driving firm-level innovation, while Bernstein et al. (2022b) and Glennon et al. (2022) provide evidence on how high-skilled immigrants enhance productivity across industries. Additionally, Dimmock, Huang, and Weisbenner (2022) highlight the long-term effects of immigration policy on firm innovation, showing the positive impact of immigrant talent on U.S. patenting and overall market competitiveness.

Determinants of startup success have been extensively studied, with financing identified as a key driver. Hall and Lerner (2010), Kaplan and Strömberg (2003), and W. R. Kerr, Lerner, and Schoar (2011) examine the critical role of venture capital and angel investment in startup growth, while Bernstein, Korteweg, and Laws (2017) and Corradin and Popov (2015) discuss alternative sources of funding such as home equity and its impact on entrepreneurial potential. Work experience, peer effects, and founding team composition are also important factors, as noted by Gompers, Lerner, and Scharfstein (2005), Elfenbein, Hamilton, and Zenger (2010), and Ewens and Marx (2018). Finally, Bernstein et al. (2022a) explore how local business opportunities shape startup performance, particularly in markets with high entrepreneurial activity.

3 Data and Sample Construction

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

3.1 Data

Our research primarily relies on two databases: Revelio Lab and Crunchabse. We rely on Crunchbase database to collect information on startups. It presents comprehensive firm-level information: 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; S. Lee and Kim 2023; Gofman and Jin 2024), Crunchbase is well-positioned to capture startup activities.

We use Revelio Labs to collect individual information. 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. Amanzadeh, Kermani, and McQuade (2024) find that over 80% of college-educated individuals in the US have LinkedIn profiles. 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., S. Lee and Kim 2023; Jeffers 2024; Gofman and Jin 2024).

To identify migrant entrepreneurs in 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 "co-founder". Next, to construct a measure of migrant, we follow 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 migrant entrepreneur in our sample. Our measure of migrants could miss the individual who are migrants but with the LinkedIn initial country being the US. Thus, the number of migrant entrepreneurs in our sample represents the lower bound of the actual number of migrant entrepreneurs.

3.2 Sample counstruction

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

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 LinkedIn 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 Revelio Lab and Crunchbase datasets.

After merging, we keep the US-based firms that are either labeled as the US firms by Crunchbase or have at least one founder with job location in the US. In addition, to remove potential fake LinkedIn accountants, 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. Additionally, we exclude firms that have not had any employees (excluding founders) within three years of their inception to avoid including shell firms. This process results in a sample of 134,761 distinct entrepreneurs who founded 90,834

startups in the US between 2000 and 2022.

3.3 Migrant Entrepreneurs in the US from 2000 to 2022

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 this period. First, the share of migrant entrepreneurs have been steadily increasing from about 12% in 2000 to 27% in 2022. The shares of migrant entrepreneurs at different point in time are largely consistent with those report in Chodavadia et al. (2024). In addition, Figure 1 breaks down the composition of four categories of migrant entrepreneurs: (1) migrant entrepreneurs who establish startups without co-founding with others (*Migrant_Single*), (2) migrant entrepreneurs who co-found startups with native entrepreneurs (*Migrant_Native*), (3) migrant entrepreneurs who co-found startups with migrant entrepreneurs from the same home countries (*Migrant_co-found_Migrant_Same_HomeCountry*), and (4) migrant entrepreneurs who co-found startups with migrant entrepreneurs from the different home countries (*Migrant_co-found_Migrant_Diff_HomeCountry*). Except for *Migrant_Single*, the shares of the other three types of migrant founders have been increasing, whereas the share of *Migrant_Single* has been quite stable over the past decades.

Panel A of Figure 2 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 a 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 2 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 A of Figure 3 displays the top ten industries based on the number of startups founded by migrant entrepreneurs. 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.[1] The top three industries for startups founded by migrant entrepreneurs are *sales and marketing* (1,886 startups), *commerce and shopping* (1,857 startups), and *software* (1,831 startups). Panel B of Figure 3 highlights the top ten industries based on the proportion of startups founded by migrant entrepreneurs relative to the total number of startups in each industry. *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.

3.4 Summary statistics

Table 1 compares the characteristics of native with 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 these degrees being earned from top 50 and top 100 universities. Additionally, in terms of prior work experience before starting new ventures, migrant entrepreneurs are more likely to have held managerial, engineering, or scientific positions. Conversely, they are less likely to have experience in finance, marketing, sales, or operations.[2]

Table 2 presents summary statistics at firm level for the sample used in our analyses in the next section. The sample includes 22,967 startups founded between 2000 and 2017 that have at least two co-founders. The sample stops in 2017 to allow for a minimum of five years to assess

[1] 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

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

two key outcome variables: the probability of acquisition within five years of inception and the likelihood of an IPO within ten years of inception. To ensure a fair comparison between startups co-founded by migrant and native entrepreneurs and those founded solely by native entrepreneurs, we exclude startups established by a single founder. This adjustment accounts for the possibility that promising projects may attract additional founders.[3]

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. On average, startups hire 26 employees in three years since the firm inception year. Within the first five years of the establishment year, 30% of startups' workforce consists of migrant employees, 30% hold technology-related positions (i.e., engineer or scientist roles classified by Revelio Lab), 28% have a bachelor's degree as their highest level of education, and 18% hold a master's, MBA, or PhD degree. Within the first three years of the inception year, 36% of startups have received external financing with average funding amount of 38 million US dollars and 18% have received financing from VCs based outside of the US. About 6% of startups are acquired within the five years of establishment, and approximately 1% of firms go public within the ten years of establishment.

4 Migrant Entrepreneurs and Startup Performance

In this section, we present baseline results of comparing the performance of startups founded by migrant entrepreneurs with those by native entrepreneurs. We start our analyses by investigating whether the performance of startups differs based on whether they were founded by migrant or native entrepreneurs. Additionally, we examine whether performance varies between startups founded solely by migrant entrepreneurs and those co-founded by both migrant and native entrepreneurs.

[3]Table A2 in Appendix presents summary statistics for startups founded by both single and multiple founders.

4.1 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 ($ln(Raised_{[t,t+3]})$), 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:

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

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, $\alpha_{j,t}$ is the industry$\times$inception year fixed effects, $\boldsymbol{X}_{i,t}$ represent a set of control variables: 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*), an indicator that is equal to one if at least one of the founders previously held a managerial positions (*Manager*), 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 (*Top50_University*). The robust standard errors are clustered at industry$\times$year level.

The estimates of β_1 and β_2 examine the impact of migrant entrepreneurs on startup performance. β_1 alone in equation (1) measures the effect of migrant founders on startup performance

compared 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.

4.2 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 evaluate the impact of the presence of 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. 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 founded by migrants in three years after the inception 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 migrant and native founders perform better than those founded solely by migrant founders. The coefficient on *Migrant_Native* is 0.083, statistically significant at 1% level, and the coefficient on *Migrant* reduces from 0.2 in column (1) to 0.147 and remains statistically significant at 1% level. These results suggest that migrant-native-co-founded startups' employment size in 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 es-

tablishment. 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 0.067 and statistically significant at 1% level. As for the economic significance, 0.067 represents a 18.6% increase relative to the sample average of the dependent, $Funded_{[t,t+3]}$. 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 0.188, 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 0.18 significant at the 1% level.

We examine the acquisition outcome in columns (7) and (8). In column (7), we do not find significant impact of migrant entrepreneurs on the likelihood of acquisition within five years of establishment as the coefficient on *Migrant* is statistically insignificant. Column (8) shows that the chance of getting acquired for migrant-only startups is 1.9% lower than native-only startups, while migrant-native-co-founded startups have a 2.5% higher acquisition likelihood compared to native-only startups. These results suggest that migrant-native-co-founded startups have a 0.6% ($= 2.5\% - 1.9\%$) higher chance to be acquired within five years of inception than native-only startups. This represents a 10% increase relative to the sample average of $Acq_{[t,t+5]}$. In addition, the 0.6% higher chance is statistically significant at 10% level.

Finally, columns (9) and (10) show the impact of migrant entrepreneurs on the chance 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

larger employment sizes compared to native-founded ones, with migrant-native-co-founded startups showing the largest employment size. 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 significant 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 have a lower likelihood than native-only startups. Lastly, while migrant-only startups show no increase in IPO likelihood, 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.

4.3 Robustness checks of baseline results

In this section, we examine whether our baselines results are robust to various sample selection and specifications. Panel A of Table A3 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 baseline results presented in Table 3.

In Panel B of Table A3, we select startups that have already received external funding within the three years of their inception. We then conduct the analyses on these firms conditional on 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 baseline results presented in Table 3.

Panel C of Table A3 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 poten-

tial estimation bias arising from log-liner 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 A3 are consistent with the baseline results obtained using OLS estimation.

5 Mechanisms

In this section, we explore the potential mechanisms that explain why migrant-native co-founded startups outperform migrant-only startups, and why migrant-only startups demonstrate superior performance compared to native-only startups. Specifically, we consider the following three explanations:

1. **Access to labor pool**: A key advantage of migrant-founded startups over native-only startups is their ability to access a broader and more diverse labor pool. Migrant founders often have stronger connections to migrant workers, who may offer specialized skills or be available at lower labor costs. In the case of migrant-native co-founded startups, they can leverage the strengths of both migrant and native co-founders, granting them dual access to labor markets. This enables them to scale more quickly, attract a diverse talent pool, and respond more effectively to various operational needs. Additionally, a more diverse workforce can foster greater innovation, as individuals from different backgrounds bring varied perspectives and approaches to problem-solving.

2. **Access to investors**: Migrant-founded startups may also benefit from increased access to foreign capital, which can contribute to their success. Migrant founders often maintain connections with investors in their home countries, offering access to a broader and potentially untapped funding network that native founders may lack. This foreign investment is particularly valuable when local capital is constrained, or when investors with international market knowledge better understand the startup's growth potential. Migrant-native co-founded startups may have an advantage in attracting both domestic and international investment, allow-

ing them to secure more capital at favorable terms and enhancing their financial resilience and growth prospects.

3. **Access to product markets**: Lastly, migrant-founded startups are uniquely positioned to access foreign markets. Migrant founders can leverage their knowledge of and connections in international markets, enabling the startup to expand beyond domestic borders. While migrant founders may have an inherent advantage in accessing foreign markets, startups with both migrant and native co-founders may benefit from a unique synergy. 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.

5.1 Superior performance of migrant-native startups

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.

5.1.1 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 screening migrant workers, and whether native founders are more effective at screening native workers. Employee quality is measured by the number of workers hired within the first five years of the firm's inception who are subsequently promoted within

three years of joining. To address potential concerns about internal biases, 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 are more likely to be merit-based and less influenced by favoritism, offering a more objective measure of employee quality.

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 0.552 (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 (-0.278, 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-co-founded firms still hire 27.4% more migrant employees ($= 100 \times (0.552 - 0.278)$), representing a 91% increase compared to the sample average.

In columns (2) to (4), we present Poisson regression estimates using internal promotions as a proxy for labor quality. Column (2) examines the effects on the total number of high-quality workers hired within the first five years of a startup's inception. The coefficients on both *Migrant* and *Migrant_Native* are positive and statistically significant at the 1% level, indicating that migrant-only startups hire more high-quality workers than native-only startups, and migrant-native startups hire more high-quality workers than migrant-only startups. These results align with our baseline findings, where migrant-native startups exhibit the best overall performance, followed by migrant-only startups. In columns (3) and (4), we further disaggregate the total number of high-quality workers into migrant and native workers, respectively. The coefficients on *Migrant* show mixed results: migrant-only startups are positively associated with the number of high-quality migrant workers in column (3) (1.284, significant at the 1% level), but negatively associated with the number of high-quality native workers in column (4) (-0.920, significant at the 1% level).

These results suggest that migrant founders are more adept at screening migrant workers

but face challenges in hiring high-quality native workers. The coefficient on *Migrant_Native* is -0.28 and statistically significant at the 1% level, indicating that migrant-native startups hire fewer high-quality migrant workers compared to migrant-only startups. However, relative to native-only startups, migrant-native startups still hire 73% more high-quality migrant employees ($= 100 \times (e^{1.294-0.28} - 1)$). In column (5), the coefficient on *Migrant_Native* is 0.827 and statistically significant at the 1% level. This magnitude is comparable to the negative coefficient on *Migrant* (-0.92), suggesting that in migrant-native startups, native co-founders complement migrant co-founders in screening and hiring native workers, thereby offsetting the challenges faced by migrant-only startups in this regard.

In columns (5) to (7), we present Poisson regression estimates using promotions after employees transition to new firms as a proxy for labor quality. Unlike internal promotions, which may be influenced by biases such as favoritism, external promotions are more likely to reflect employees' skills and merit. 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 screening migrant employees, native founders are better at screening native employees, and migrant-native startups leverage the strengths of both groups.

5.1.2 Combine strengths in foreign and domestic VC market

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 and 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 12.3% more likely to receive funding from foreign VCs compared to native-only startups. The coefficient on *Migrant* is 0.123, 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 (-0.037, 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 8.6% ($= 100 \times (0.123 - 0.037)$) 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 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. The results show a mixed pattern for migrant-only startups: they are positively associated with the number of top foreign VCs (coefficient of 1.533, significant at the 1% level) in column (3), but negatively associated with the number of domestic VCs (coefficient of -0.361, significant at the 1% level) in column (4). This indicates that migrant-only startups are more favored by foreign VCs, but less favored by domestic VCs. Meanwhile, the coefficient on *Migrant_Native* is -0.344 and statistically significant 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 ($= 100 \times (e^{1.533-0.344} - 1)$). In column (5), the coefficient on *Migrant_Native* is 0.501 and statistically significant at the 1% level, which is comparable to the magnitude of the negative coefficient on *Migrant* (-0.361), suggesting that native co-founders in migrant-native startups complement migrant co-founders in attracting top domestic VCs.

Finally, 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.

5.1.3 Combine strengths in foreign and domestic product market

Last, we provide evidence about 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 the 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 1% level, indicating that migrant-only startups have 41% (=$100 \times (e^{-0.527} - 1)$) fewer granted patents overall than native-only startups. The coefficient on *Migrant_Native*, however, is positive and significant at 1% level, implying that the number of grant patents filed by migrant-native startups is 117% (=$100 \times (e^{0.777} - 1)$) more than those by migrant-only ones and 28.4% (=$100 \times (e^{0.777-0.527} - 1)$) 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 (-0.435, 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 0.622 (significant at the 1% level). This indicates that the number of granted patents filed in the US by migrant-native startups is 86% (=$100 \times (e^{0.622} - 1)$). 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 significant, 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.

5.2 Heterogeneous effects

Next, we explore heterogeneous effects of migrant founders on startup performance. Specifically, we consider three dimensions: 1) share of migrant labor from the founders' home country in a given industry-state-year, share of financing deals involving VCs from the migrant founder's home country in a given industry-year, and the share of granted patents filed by the US firms in the migrant founder's home country in a given industry-year.

Panel A of Table 7 explores whether the performance of migrant-founded startups varies based on the local labor share of employees from the migrant founder's home country. The key independent variable of interest is *High_Emp_Share_Home_Country*, which is an indicator for industries and states with a high labor share (above the median value) of migrant employees from the same

non-US country as the migrant founder. The dependent variables capture various dimensions of firm performance, including employment size, funding outcomes, acquisitions, and IPO activity.

Figure 4 illustrates the migrant labor share across industries and the home countries of migrant employees in four key states: California, New York, Massachusetts, and Texas. The figure presents ten migrant employee home countries that are the top ten migrant founders' home countries shown in Figure 2. As shown in Figure 4, migrant workers from India, the UK, Canada, and China contribute significantly to the US migrant labor force. Furthermore, these workers are distributed across a wide range of industries, rather than being concentrated in just a few sectors.

Columns (1) through (5) in Panel A of Table 7 report the impact of migrant entrepreneur on the five measures of startup performance. The coefficients on *High_Emp_Share_Home_Country* across all of the five columns are positive and significant at the 10%, 5%, or 1% level, indicating that migrant-founded startups located in industries and states with a high share of employees from the migrant founder's home country perform significantly better migrant-founded startups located in industries and states with a corresponding low share.

The results from Panel A of Table 7 suggest that migrant entrepreneurs benefit from access to migrant labor pools, particularly in industries and states with a high concentration of workers from the founder's home country. Migrant-founded firms hire disproportionately more migrant and technical workers, while migrant-native co-founded firms display a more balanced workforce composition. Moreover, migrant entrepreneurs in regions with strong home-country networks experience improved performance in terms of employment growth, funding success, and exit outcomes. These findings highlight the critical role of migrant networks in shaping the labor composition and performance of startups.

Panel B of Table 7 explores the performance of migrant-founded startups in industries where the share of financing deals involving VCs from the migrant founder's home country is high. The key variable of interest in this table is *High_VC_Share_Home_Country*, which is an indicator that equals one if the share of deals in the industry that are invested by foreign VCs from the migrant founder's home country is above the median value in a given year. Figure 5 illustrates the non-US-

VC share across industries and the home countries of migrant employees. The figure presents ten countries that are the top ten migrant founders' home countries shown in Figure 2. As shown in Figure 5, investors from the UK, Canada, Israel, France, and China contribute significantly to the US VC market. Furthermore, the deals financed by the VCs from these countries are distributed across a wide range of industries, rather than being concentrated in just a few sectors.

The results in Panel B of Table 7 show that *High_VC_Share_Home_Country* is positively associated with greater employment size (coefficient: 0.078, significant at the 5% level), increased funding likelihood (coefficient: 0.049, significant at the 1% level), more funds raised (coefficient: 0.265, significant at the 1% level), a higher likelihood of acquisition (coefficient: 0.014, significant at the 5% level). and a higher chance of going public (coefficient: 0.006, significant at the 10% level). These results highlights that migrant-founded startups tend to perform better in industries where a larger share of the financing comes from investors based in the migrant founder's home country. This implies that migrant founders benefit from strong investor networks tied to their home countries, which may provide capital, mentorship, and other resources that drive the startup's growth, funding opportunities, and potential acquisition and IPO.

Panel C of Table 7 shifts the focus toward industry heterogeneity by examining whether the effect of migrant founders on startup performance varies depending on the share of granted patents filed by the US firms in the migrant founder's home country (captured by *High_Patent_Share_Home_Country*). The underlying hypothesis is that industries in migrant founders' home countries, where a high share of patents are filed by the US firms, are likely appealing to the US companies in the same sectors due to factors such as a large and growing consumer base, favorable regulatory environments, and lower production costs. Consequently, startups founded by migrants from these countries may find it easier to access these foreign markets, thereby enhancing their overall performance.

Figure 6 illustrates the share of granted patents filled by the US firms across industries and non-US counties where the patents are filled. The figure presents ten patent filling countries that are the top ten migrant founders' home countries shown in Figure 2. As shown in Figure 6, patents filed by the US firms in Canada, Australia, and China constitute a significant portion of the patents

filed in non-US countries by the US firms. Furthermore, the patents filed in these countries are distributed across a wide range of industries, rather than being concentrated in just a few sectors.

In Panel C of Table 7, across the five dependent variables, employment size, funding received, amount of funding, acquisition, and IPO likelihood, the results reveal that the coefficients on *High_Patent_Share_Home_Country* are positive and statistically significant in Column 3 (funding amount), Column 4 (acquisition), and Column 5 (IPO) at either 10%, 5%, or 1% level, suggesting that migrant-founded startups in industries with high patenting activity in migrant founders' home countries have stronger performance than migrant-founded startups without operating in such industries. For example, the coefficient of 1.461 for ln(Raised) implies that these startups secure more funding, while the positive coefficients for acquisition (0.148) and IPO (0.251) suggest a greater likelihood of successful exits in these industries.

The results in Table 7 indicate that migrant-founded startups thrive in environments with a high concentration of labor from their home countries, showcasing improved performance in employment size, funding, acquisitions, and IPOs. Additionally, the presence of substantial financing from VCs associated with the founders' home countries correlates with greater startup success, highlighting the importance of investor networks. Furthermore, startups in industries with high patenting activity in the founders' home countries also demonstrate superior performance, underscoring the advantages of operating in markets that align with their home country's strengths. Collectively, these findings emphasize that the combination of migrant networks and domestic resources significantly enhances the success of migrant-founded startups.

6 Instrumental Variable Approach

Our baseline results indicate that migrant-founded, especially migrant-native-co-founded startups, exhibit superior performance compared to their native-founded counterparts. This finding, however, could result from migrant founders' self-selection. Compared to native individuals, the entry costs for migrants to become entrepreneurs might be substantially higher due to factors such as

language differences, cultural adaptation, and limited access to local financial and social networks. As a result, migrants may be more selective than natives in choosing entrepreneurial ventures, focusing only on high-potential projects that justify the additional challenges they face. In this section, we address the potential endogeneity issues by employing instrumental variable approach.

6.1 Instrumental variable construction

We construct an instrumental variable to account for the superior performance of startups co-founded by both migrant and native founders. To capture the exogenous variation in these co-founded startups, we explore the variation in the proportion of native students among those who obtained their highest degree from the same US university, enrolled in the same year, earned the same degree, and belong to the same racial group. Specifically, for a native entrepreneur i with race r (White, Asian, Black, Hispanic, and Native provided by Revelio Lab) 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 ratio:

$$Cohort_Native_Share_{i,u,d,r,t} = \frac{Native_{u,d,r,t} - 1}{Native_{u,d,r,t} + Foreign_{u,d,r,t} - 1} \tag{2}$$

where $Native_{u,d,r,t}$ is the number of native students with race r who obtained degree d at the US university u with enrollment year t, $Foreign_{u,d,r,t}$ is the number of international students with race r who obtained degree d at the US university u with enrollment year t. We subtract one in both numerator and denominator to remove the impact of native entrepreneur i on the ratio. In Panel A of Table 8, the sample average of *Cohort_Native_Share* is 0.95, which is in line with international students constituting about 5% of the US college graduates that is reported by the Institute of International Education.[4] Table IA.1 in the Internet Appendix presents 20 university-degree-race observations with lowest *Cohort_Native_Share* in 2010.

The predictive power of our IV primarily comes from a strong tendency for individuals to

[4]For more informaiton, plesee see https://opendoorsdata.org/data/international-students/enrollment-trends/

co-found startups with others of same universities where they obtained the highest degrees. In Panel A of Table 8, we show that for startups with least two co-founders, about 30% of them with co-founders obtained the highest degrees from the same US university. Moreover, cognitional on attending the same university, 86% of startups' founders enrolled in the same year, 74% share the same race, and 91% obtained the same degree. Once attending the same university, the much stronger tendency for entrepreneurs to collaborate with others in the same degree program, same enrollment year, and the same race justifies that we construct the IV along these dimensions.

Second, even for natives who do not co-found with entrepreneurs from the same cohort defined above, our IV may also have influences on natives' decision regarding whether to co-found with migrants. When native students have the opportunity to interact with international students of the same cohort, it effectively broadens their social network to include foreign members and reduce cultural and communication barriers to collaborate with foreigners, both of which could increase the likelihood that they will co-found startups with migrants in the future.

The identification assumption is that the proportion of native students in this specific setting affects the likelihood that a migrant founder will co-found with a native partner but does not directly influence the startup's subsequent performance. This assumption hinges on the idea that the composition of the student body, in terms of native versus migrant proportions, affects the probability of collaboration between migrants and natives through increased opportunities for interaction during their education. However, this variable should be unrelated to unobservable factors that could drive startup success, such as the self-selection issue discussed above, ensuring that any correlation between the instrument and startup performance arises through its impact on migrant-native partnerships rather than other channels.

6.2 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 one native founder. Specifically, we estimate the following 2SLS specification:

$$Migrant_Native_{i,t} = \beta Cohort_Native_Share_{i,t} + \mathbf{\Gamma'} \boldsymbol{X}_{i,t} + \alpha_{j,t} + Edu\ FE + \varepsilon_{i,t} \tag{3}$$

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

The instrumental variable $Cohort_Native_Share_{i,t}$ is at startup level. If a startup has multiple native co-founders, we take the maximum value of *Cohort_Native_Share*. $\alpha_{j,t}$ is the industry×est. year fixed effects and $\boldsymbol{X}_{i,t}$ represent a set of control variables same as those in equation (1). *Edu FE* represents two sets of fixed effects: degree×enrollment year and university fixed effects, which correspond to a native founder's degree type of the highest degree obtained at a US university with a given enrollment year. If a startup has multiple native co-founders who belong to different cohorts (i.e. university-degree-race-year), we choose the set of university, degree, and enrollment year that are based on the native founder with the highest IV.

Panel B Table 8 reports the first-stage regression results, where *Cohort_Native_Share* is used to predict the likelihood of a startup being co-founded by migrant and native founders (*Migrant_Native*), as well as the second-stage results for startup performance measures. Column (1) presents the estimates of the first-stage. The coefficient on the IV, *Cohort_Native_Share*, is -0.657 and statistically significant at the 1% level. These results indicate 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. The strength of the instrument is further confirmed by the Wald F-statistics, which is 143, exceeding the conventional threshold of ten for instrument relevance. Thus, the IV is unlikely to subject to weak instrument issue.

Columns (2) through (6) 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 0.426 (significant at the 5% level), suggesting that migrant-native-co-founded startups exhibit about a 40% larger employment size after three years, relative to native-only startups. The outcome variables in column (3) is the probability of receiving external funding within three years of startup establishment. The instrumented coefficient on *Migrant_Native* is 0.268,

significant at 1% levels, implying that migrant-native-co-founded startups are about 27 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 1.006 (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 the second-stage estimates for the share of migrant employees, probability of getting funded by foreign VCs, and the probability of filing patents in non-US countries that are eventually granted. In column (1), the coefficient on $\widehat{Migrant_Native}$ is 0.624, statistically significant at 1% level, suggesting that the share of migrant employees within the first five years of the startup inception for migrant-native-co-founded startups is about 0.63 higher than that of native-only startups. In column (2), 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-co-founded startups are about 16% more likely to receive foreign-VC funding than native-only ones. The point estimate is statistically significant at 5% level. In column (3), 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. However, we do not find a statistically significant impact on overseas patenting. Since filing a overseas patent is a rare event in our sample (i.e., about 2% of firms have granted foreign patents that are filed within five years of their inception), the low variation in the

outcome variable could limit the power 2SLS estimation.

Since the sample in 2SLS estimation focuses on the US-college-educated entrepreneurs and startups with at least one native entrepreneur, it differs from the sample used in the baseline OLS estimation. To compare OLS estimates with 2SLS estimates, in Panel A of Table A4, we also report the OLS estimates based on the sample that is same as that use in the 2SLS analyses. Overall, the estimates of OLS regressions are consistent with the baseline results reported in Table 3. The 2SLS estimates are about two to five times larger than the OLS estimates across eight specifications in Panel A of Table A4.

Overall, the 2SLS results demonstrate that migrant-native-co-founded startups, compared to native-only startups, experience significantly higher employment growth, more likely to secure funding within three years of establishment, raise a significantly larger amount of funding, hire disproportionally more migrant employees, and are more likely to receive funding from VC based outside of the US. However, 2SLS estimates show no significant effects of migrant-native-co-founding on acquisition, IPO, and overseas patenting outcomes, likely due to low variation in these rare outcomes, which limit the precision and power of the estimates.

6.3 Robustness checks: 2SLS estimates

In this section, we conduct addtional analyses to check the robustness of 2SLS estimates with various sets of fixed effects. We consider four alternative sets of fixed effects. The first one contains only Industry×Est. Year fixed effects. The other three ones, on the top of Industry×Est. Year fixed effects, contain different combination of fixed effects related to native founder's university, degree, and enrollment year. These four sets of fixed effects are: (1) university, enrollment year, and degree fixed effects, (2) university×degree and enrollment year fixed effects, and (3) university×enrollment year and degree fixed effects. We apply each of these four sets fixed effects one by one to equation (3) and (4).

Panel B of Table A4 reports the first-stage regression results, where *Cohort_Native_Share* is used to predict the likelihood of a startup being co-founded by migrant and native founders (*Mi-*

grant_Native). Specifications vary across the columns in terms of fixed effects. Column (1) includes only Industry×Est. Year fixed effects, while subsequent columns progressively add more stringent fixed effects discussed above. Across all specifications (columns 1-5) with different sets of fixed effects, the IV exhibits a strong, statistically significant relationship with the endogenous regressor, with negative coefficients ranging from -0.704 to -0.590, all significant at the 1% level. These results indicate that a higher proportion of native students in a university cohort decreases the likelihood of migrant-native co-founding. The strength of the instrument is further confirmed by the Wald F-statistics, which range from 68.5 to 259.4, exceeding the conventional threshold of ten for instrument relevance. Thus, the IV is unlikely to subject to weak instrument issue. In addition, we report partial R^2 that demonstrates the IV's variation that is used to predict *Migrant_Native* with different sets of fixed effects.

In Panels C, D, E, and F, we present the 2SLS results with four alternative sets of fixed effects, respectively. The results in all of the four panels are largely consistent with the 2SLS results reported in Table 8 with the set of fixed effects including: Industry×Est. Year, Degree×Enrollment Year, and University fixed effects.

7 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 indi-

cate 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. A variety of heterogeneity tests provide further evidence supporting these underlying mechanisms.

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Figure 1: Percentage of Migrant Entrepreneurs in the US from 2000 to 2022

This figure shows the percentage of migrant entrepreneurs over all entrepreneurs who established startups in the US in each year from 2000 to 2022. *Migrant_Single* indicates migrant entrepreneurs who establish startups without co-founding with others. *Migrant_Native* indicates migrant entrepreneurs who co-found startups with native entrepreneurs. *Migrant_co-found_Migrant_Same_HomeCountry* indicates migrant entrepreneurs who co-found startups with migrant entrepreneurs from the same home countries. *Migrant_co-found_Migrant_Diff_HomeCountry* indicates migrant entrepreneurs who co-found startups with migrant entrepreneurs from the different home countries.

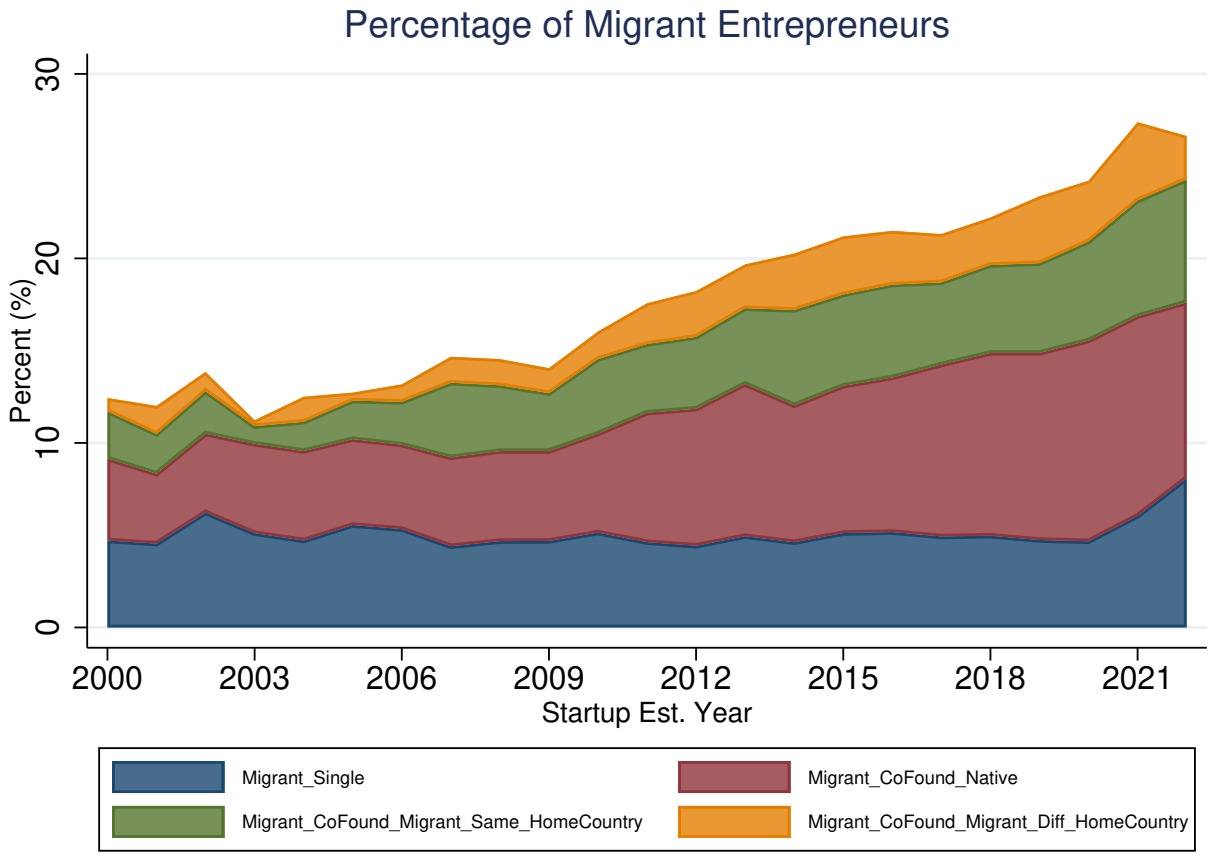
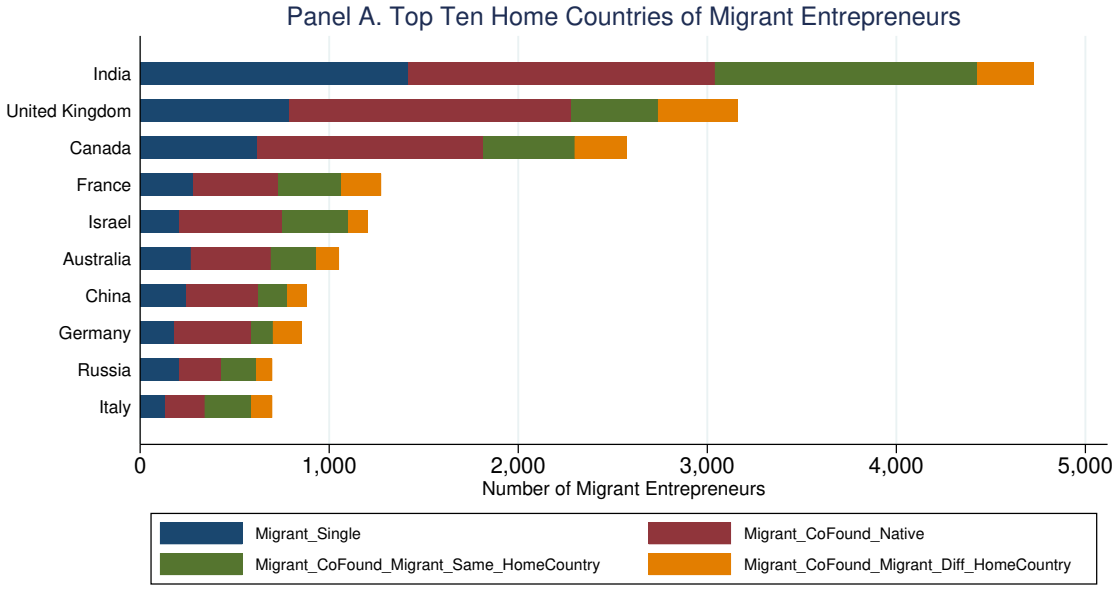


Figure 2: Top Ten Home Countries of Migrant Entrepreneurs in the US

This figure 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. *Migrant_Single* indicates migrant entrepreneurs who establish startups without co-founding with others. *Migrant_Native* indicates migrant entrepreneurs who co-found startups with native entrepreneurs. *Migrant_co-found_Migrant_Same_HomeCountry* indicates migrant entrepreneurs who co-found startups with migrant entrepreneurs from the same home countries. *Migrant_co-found_Migrant_Diff_HomeCountry* indicates migrant entrepreneurs who co-found startups with migrant entrepreneurs from the different home countries.



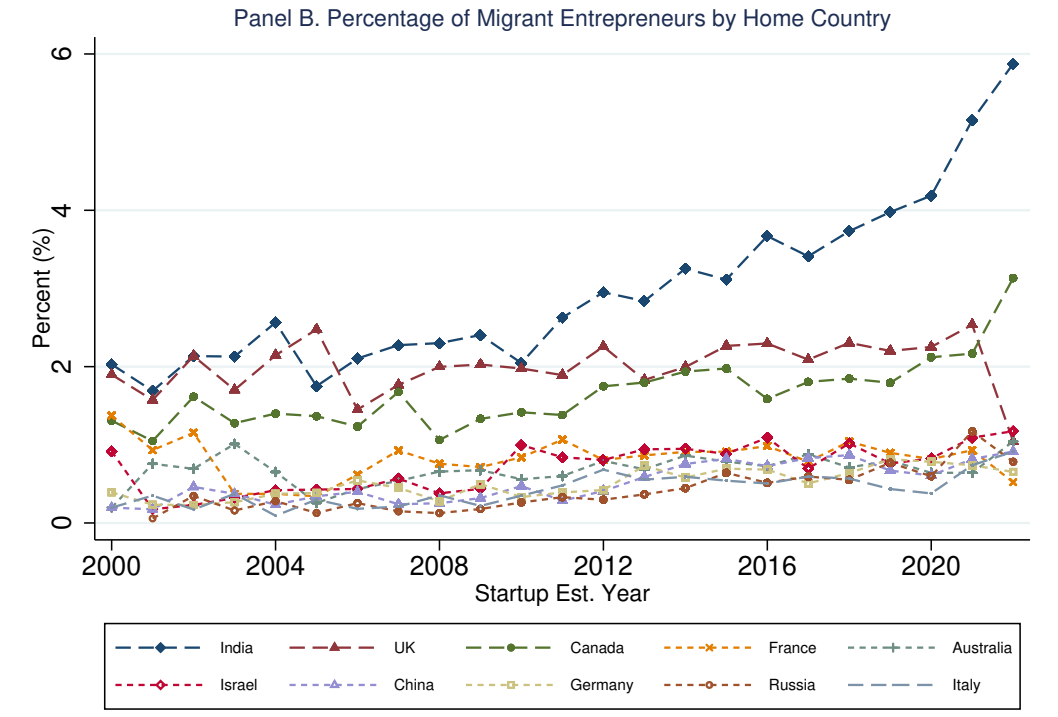


Figure 3: Top Ten Industries where Migrant Entrepreneurs Establish Startups in the US

This figure shows the top ten industries where migrant entrepreneurs established startups in the US from 2000 to 2022. In Panel A, the top ten industries are selected based on the total number of migrant entrepreneurs. In Panel B, the top ten industries are selected based on the percentage of migrant entrepreneurs over all entrepreneurs. The industry classification is based on that of Crunchbase database.

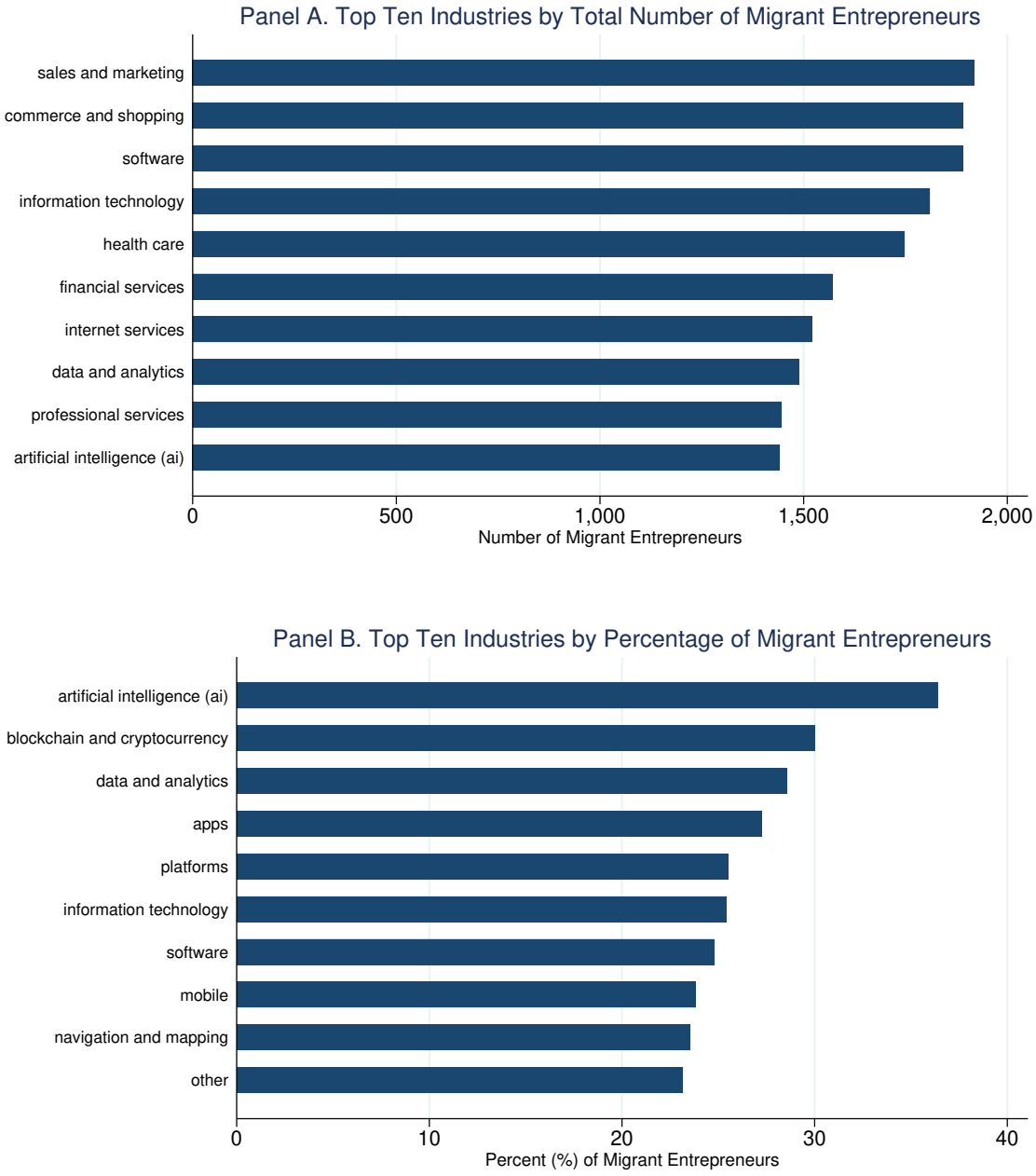
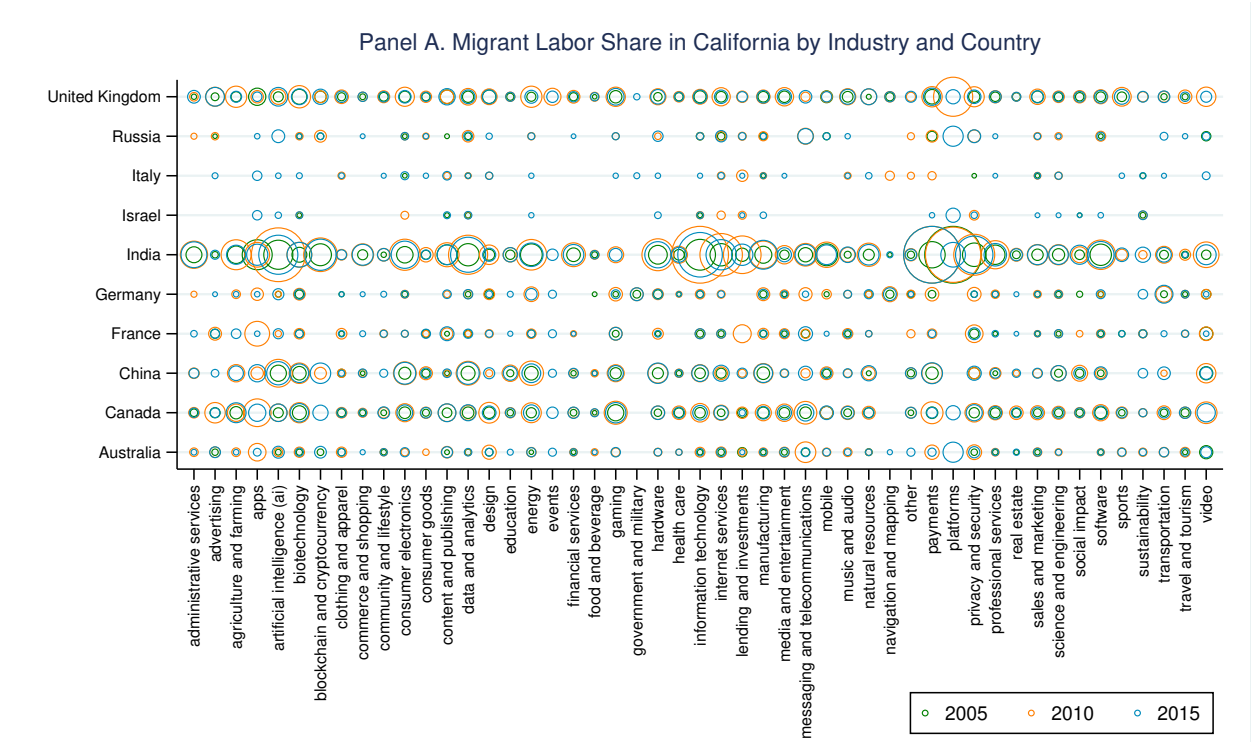
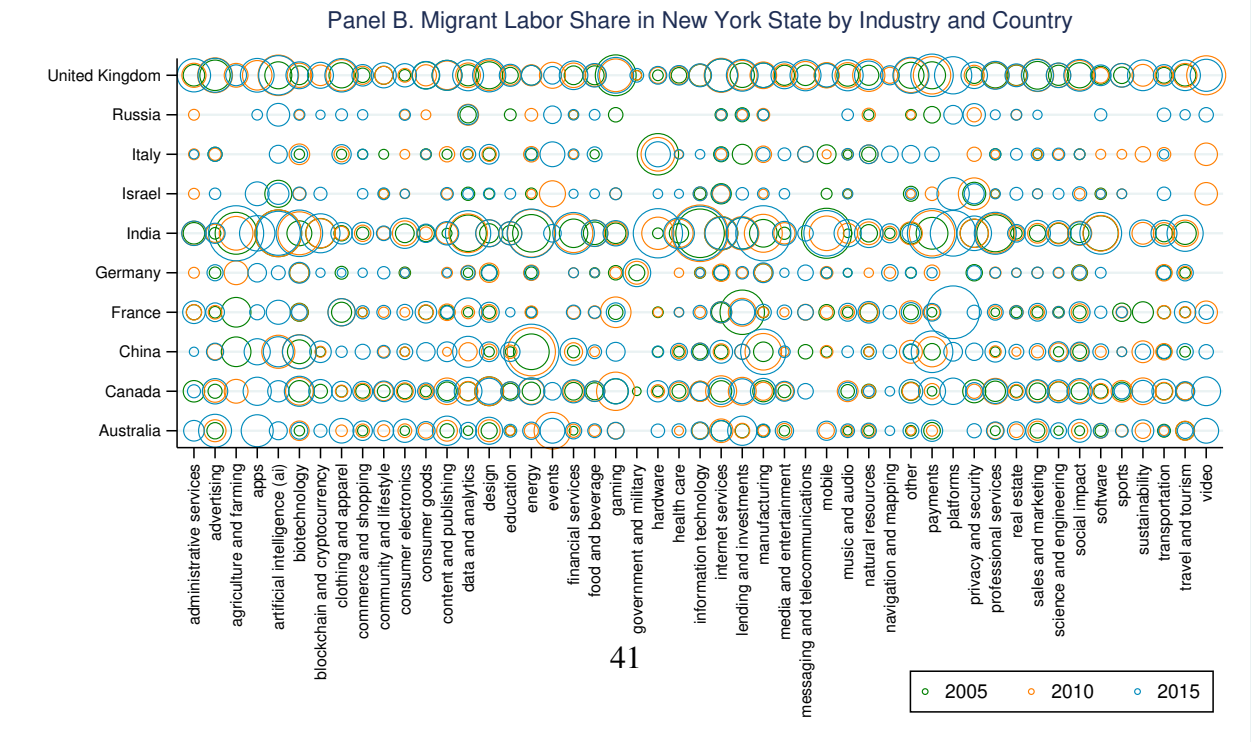
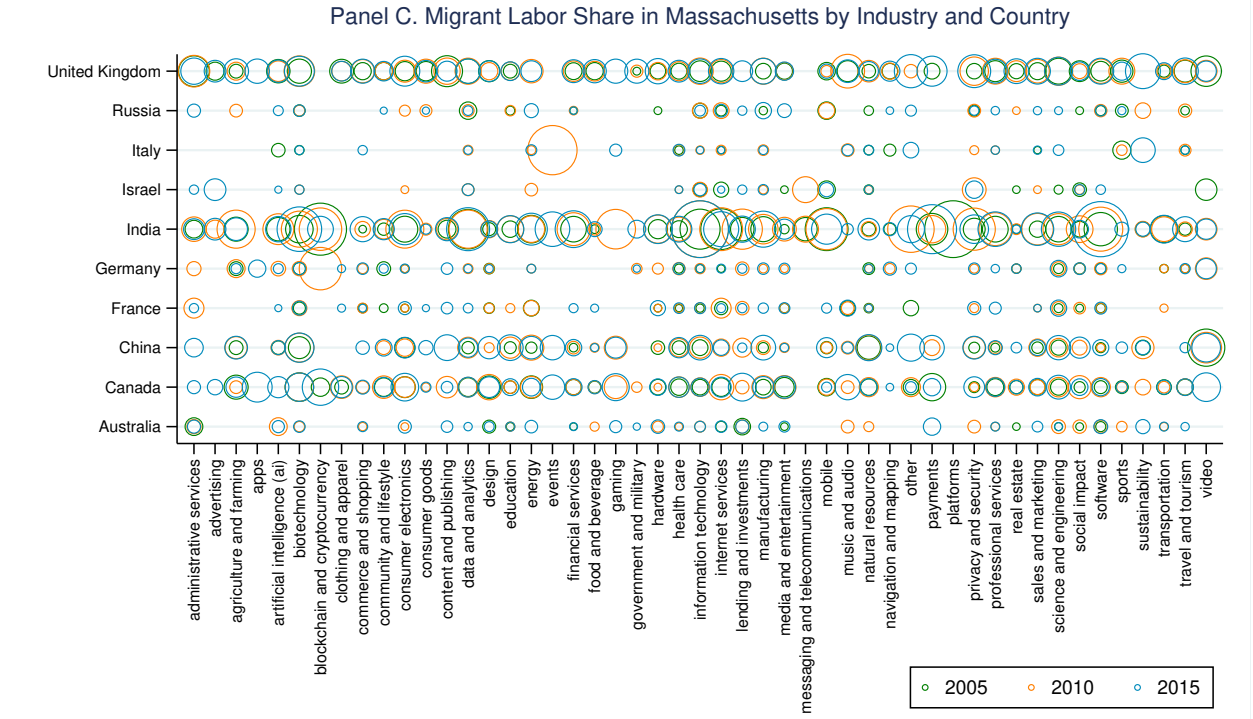


Figure 4: Migrant Labor Share

This figure shows the migrant labor share across industries and the home countries of migrant employees in four states: California (Panel A), New York (Panel B), Massachusetts (Panel C), and Texas (Panel D). The figure presents ten migrant employee home countries that are the top ten migrant founders' home countries shown in Figure 2. The circles plotted on the figure represent migrant labor shares that are above the median value for each year for migrant employees working in the US in 2005, 2010, and 2015. The size of the circles represents the relative magnitude of the migrant labor share.






Panel C. Migrant Labor Share in Massachusetts by Industry and Country
United Kingdom
Russia
Italy
Israel
India
Germany
France
China
Canada
Australia
administrative services
advertising
agriculture and farming
apps
artificial intelligence (ai)
biotechnology
blockchain and cryptocurrency
clothing and apparel
commerce and shopping
community and lifestyle
consumer electronics
consumer goods
content and publishing
data and analytics
design
education
energy
events
financial services
food and beverage
gaming
government and military
hardware
health care
information technology
internet services
lending and investments
manufacturing
media and entertainment
messaging and telecommunications
mobile
music and audio
natural resources
navigation and mapping
other
payments
platforms
privacy and security
professional services
real estate
sales and marketing
science and engineering
social impact
software
sports
sustainability
transportation
travel and tourism
video
2005
2010
2015

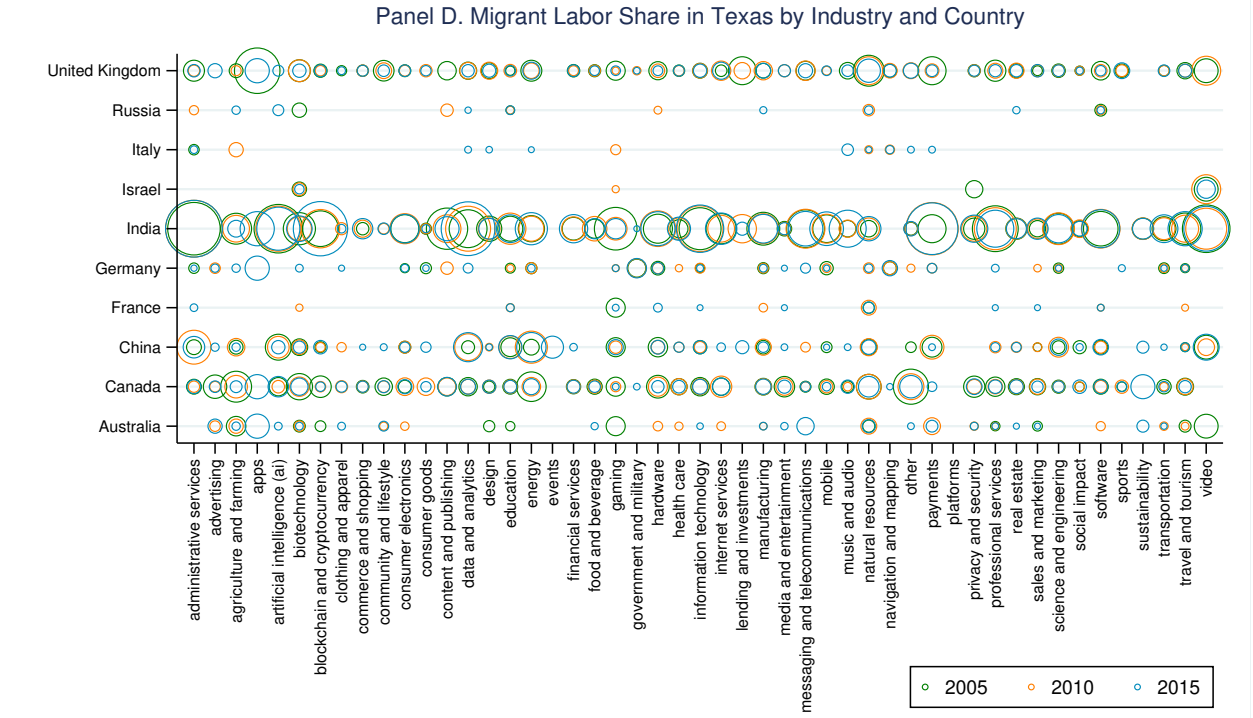

Panel D. Migrant Labor Share in Texas by Industry and Country
United Kingdom
Russia
Italy
Israel
India
Germany
France
China
Canada
Australia
administrative services
advertising
agriculture and farming
apps
artificial intelligence (ai)
biotechnology
blockchain and cryptocurrency
clothing and apparel
commerce and shopping
community and lifestyle
consumer electronics
consumer goods
content and publishing
data and analytics
design
education
energy
events
financial services
food and beverage
gaming
government and military
hardware
health care
information technology
internet services
lending and investments
manufacturing
media and entertainment
messaging and telecommunications
mobile
music and audio
natural resources
navigation and mapping
other
payments
platforms
privacy and security
professional services
real estate
sales and marketing
science and engineering
social impact
software
sports
sustainability
transportation
travel and tourism
video
2005
2010
2015

Figure 5: Foreign Investor Share

This figure plots the share of financing deals funded by non-US investors across deal industries and investor countries. The figure presents ten investor countries that are the top ten migrant founders' home countries shown in Figure 2. The circles plotted on the figure represent the shares that are above the median value for each year for deals funded by non-US investors in 2005, 2010, and 2015. The size of the circles indicates the relative magnitude of the share.

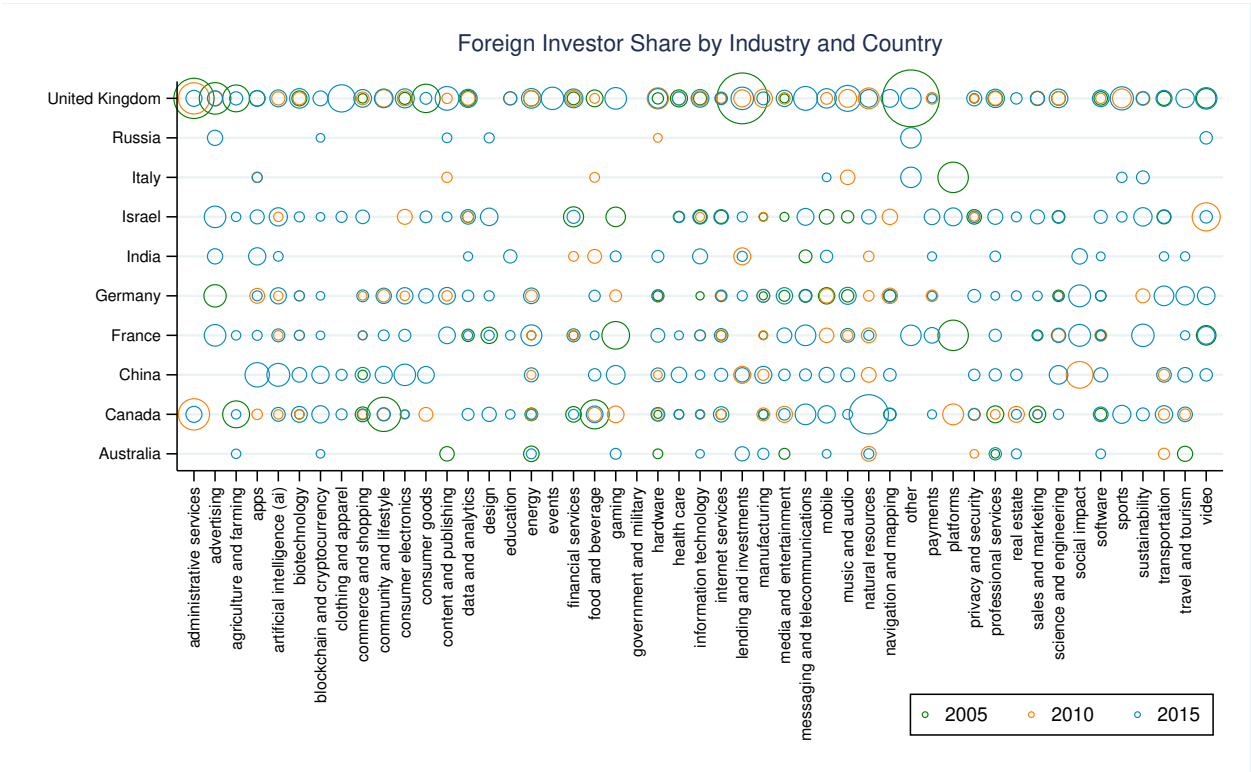


Figure 6: Share of Granted Patents Filled in Non-US Countries

This figure plots the share of granted patents filled by the US firms across industries and non-US counties where the patents are filled. The figure presents ten patent filling countries that are the top ten migrant founders' home countries shown in Figure 2. The circles plotted on the figure represent the shares that are above the median value for each year for granted patents filled by the US firms in non-US countries in 2005, 2010, and 2015. The size of the circles represents the relative magnitude of the share.

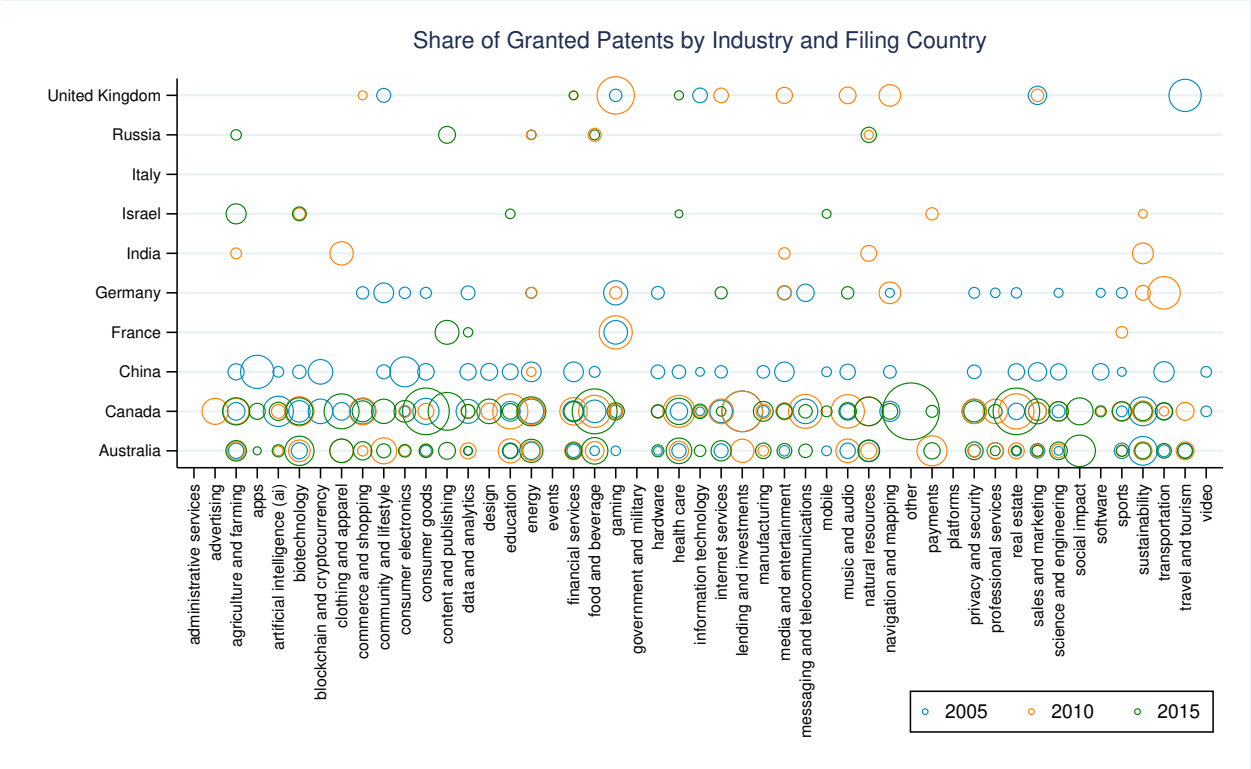


Table 1. Summary Statistics: Entrepreneur Level

This table provides the summary statistics at entrepreneurs level. The sample consists of 96,029 entrepreneurs who establish startups between 2000 and 2017 in the US. We compare the characteristics of native entrepreneurs with those of migrant entrepreneurs. Table A1 in Appendix 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 2. Summary Statistics: Startup Level

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 in Appendix provides detailed variable definitions. The firm-level summary statistics for all startups are provided in Table A2 in Appendix.

	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	38.37	167.14	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	3.41	10.59	0.00	0.00	0.00	0.00	54.00
$Foreign_Top_VC_Deal_{[t,t+3]}$	22967	0.35	1.76	0.00	0.00	0.00	0.00	12.00
$Domestic_Top_VC_Deal_{[t,t+3]}$	22967	3.01	9.71	0.00	0.00	0.00	0.00	50.00
$All_Top_VC_Exit_{[t,t+3]}$	22967	2.34	7.81	0.00	0.00	0.00	0.00	40.00
$Foreign_Top_VC_Exit_{[t,t+3]}$	22967	0.18	1.16	0.00	0.00	0.00	0.00	6.00
$Domestic_Top_VC_Deal_{[t,t+3]}$	22967	2.14	7.40	0.00	0.00	0.00	0.00	40.00
$Acq_{[t,t+5]}$	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
$All_Internal_Promotion_{[t,t+5]}$	22967	6.84	11.20	0.00	1.00	3.00	7.00	53.00
$Migrant_Internal_Promotion_{[t,t+5]}$	22967	2.03	4.07	0.00	0.00	0.00	2.00	19.00
$Native_Internal_Promotion_{[t,t+5]}$	22967	4.47	7.76	0.00	0.00	1.00	5.00	37.00
$All_Departure_Promotion_{[t,t+5]}$	22967	4.56	7.60	0.00	0.00	2.00	5.00	36.00
$Migrant_Departure_Promotion_{[t,t+5]}$	22967	1.42	2.98	0.00	0.00	0.00	1.00	14.00
$Native_Departure_Promotion_{[t,t+5]}$	22967	2.96	5.34	0.00	0.00	1.00	3.00	26.00

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 in Appendix provides detailed variable definitions.

	$Ln(Emp_{t+3})$		$Funded_{[t,t+3]}$		$ln(Raised_{[t,t+3]})$		$Acq_{[t,t+5]}$		$IPO_{[t,t+10]}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Migrant	0.203***	0.147***	0.067***	0.062***	0.188***	0.066	-0.002	-0.019***	0.004**	0.000
	(0.020)	(0.028)	(0.007)	(0.011)	(0.027)	(0.043)	(0.003)	(0.005)	(0.002)	(0.002)
Migrant_Native		0.083***		0.008		0.180***		0.025***		0.005*
		(0.029)		(0.013)		(0.046)		(0.006)		(0.003)
Bachelor	0.002	0.001	0.014**	0.014**	0.012	0.009	0.004	0.003	-0.001	-0.001
	(0.019)	(0.019)	(0.007)	(0.007)	(0.026)	(0.026)	(0.004)	(0.004)	(0.001)	(0.001)
Graduate	0.044**	0.045**	0.067***	0.067***	0.199***	0.203***	-0.002	-0.002	0.002	0.002
	(0.018)	(0.018)	(0.007)	(0.007)	(0.028)	(0.028)	(0.003)	(0.003)	(0.001)	(0.001)
Serial_Entrepreneur	0.199***	0.198***	0.073***	0.073***	0.277***	0.275***	0.009***	0.008***	0.003**	0.003**
	(0.017)	(0.017)	(0.007)	(0.007)	(0.025)	(0.024)	(0.003)	(0.003)	(0.002)	(0.002)
Manager	0.219***	0.220***	0.067***	0.067***	0.257***	0.258***	0.017***	0.017***	0.004***	0.004***
	(0.019)	(0.019)	(0.008)	(0.008)	(0.029)	(0.029)	(0.003)	(0.003)	(0.002)	(0.002)
Experience	0.005***	0.004***	-0.000	-0.000	0.006***	0.006***	0.000*	0.000	0.001***	0.001***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Number_Founders	0.091***	0.091***	0.008	0.008	0.073**	0.072**	0.002	0.002	0.001*	0.001
	(0.024)	(0.024)	(0.006)	(0.006)	(0.035)	(0.035)	(0.001)	(0.001)	(0.001)	(0.001)
Top10_University	0.328***	0.323***	0.195***	0.195***	0.998***	0.987***	0.031***	0.030***	0.016***	0.015***
	(0.029)	(0.029)	(0.011)	(0.011)	(0.056)	(0.056)	(0.007)	(0.007)	(0.004)	(0.004)
Top50_University	0.068***	0.065***	0.089***	0.089***	0.372***	0.366***	0.018***	0.017***	0.001	0.001
	(0.023)	(0.023)	(0.010)	(0.010)	(0.038)	(0.037)	(0.005)	(0.005)	(0.002)	(0.002)
Top100_University	0.011	0.010	0.022*	0.022*	0.110**	0.107**	0.004	0.003	0.001	0.001
	(0.029)	(0.029)	(0.012)	(0.012)	(0.045)	(0.045)	(0.007)	(0.007)	(0.003)	(0.003)
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	0.137	0.137	0.132	0.132	0.016	0.017	0.052	0.052

Table 4. Labor Pool Access and Labor Screening

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 number of workers hired within the first five years of a firm's inception who are subsequently promoted within three years of joining. The analysis distinguishes between internal promotions within the firm and promotions after employees have transitioned to other firms. The set of control variables is the same as that in Table 3. Column (1) presents OLS estimates, and columns (2) - (7) present Poisson estimates. 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 in Appendix provides detailed variable definitions.

		Number of Workers Internally Promoted			Number of Workers Promoted After Departure		
	$Mig_Emp_Share_{[t,t+5]}$	$All_{[t,t+5]}$	$Migrant_{[t,t+5]}$	$Native_{[t,t+5]}$	$All_{[t,t+5]}$	$Migrant_{[t,t+5]}$	$Native_{[t,t+5]}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Migrant	0.552***	0.145***	1.284***	-0.920***	0.218***	1.316***	-0.856***
	(0.007)	(0.038)	(0.038)	(0.057)	(0.038)	(0.040)	(0.057)
Migrant_Native	-0.278***	0.132***	-0.280***	0.827***	0.106***	-0.251***	0.786***
	(0.008)	(0.038)	(0.037)	(0.056)	(0.039)	(0.037)	(0.057)
Bachelor	-0.013***	0.083***	0.022	0.095***	0.068***	0.018	0.086***
	(0.004)	(0.024)	(0.027)	(0.025)	(0.026)	(0.030)	(0.028)
Graduate	0.013***	0.121***	0.150***	0.086***	0.107***	0.163***	0.064**
	(0.004)	(0.023)	(0.027)	(0.025)	(0.023)	(0.028)	(0.025)
Serial_Entrepreneur	0.027***	0.280***	0.321***	0.251***	0.266***	0.302***	0.246***
	(0.004)	(0.025)	(0.029)	(0.026)	(0.025)	(0.031)	(0.027)
Manager	0.006	0.261***	0.229***	0.262***	0.309***	0.270***	0.312***
	(0.005)	(0.029)	(0.034)	(0.030)	(0.029)	(0.033)	(0.031)
Experience	-0.002***	-0.005***	-0.007***	-0.002	-0.001	-0.007***	0.003*
	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Number_Founders	0.006***	0.031***	0.031***	0.028***	0.030***	0.032***	0.027***
	(0.001)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)
Top10_University	-0.006	0.430***	0.347***	0.491***	0.402***	0.321***	0.473***
	(0.006)	(0.029)	(0.036)	(0.031)	(0.030)	(0.035)	(0.033)
Top50_University	-0.020***	0.138***	0.045	0.207***	0.108***	-0.012	0.194***
	(0.005)	(0.029)	(0.037)	(0.030)	(0.030)	(0.036)	(0.033)
Top100_University	-0.024***	0.088**	0.027	0.132***	0.046	-0.013	0.102**
	(0.007)	(0.037)	(0.044)	(0.039)	(0.038)	(0.047)	(0.042)
Industry × Est. Year FE	Y	Y	Y	Y	Y	Y	Y
N	22912	22908	22769	22871	22896	22736	22864
Adj. R^2	0.360						
Pseudo R^2		0.110	0.191	0.112	0.108	0.188	0.105

Table 5. Investor Pool and Matching between Founders and Top VCs

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. 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 in Appendix 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	0.123***	-0.043	1.533***	-0.361***	-0.100	1.262***	-0.296***
	(0.010)	(0.066)	(0.094)	(0.071)	(0.071)	(0.115)	(0.075)
Migrant_Native	-0.037***	0.296***	-0.344***	0.501***	0.374***	-0.212*	0.494***
	(0.012)	(0.070)	(0.085)	(0.077)	(0.074)	(0.111)	(0.079)
Bachelor	0.003	0.169***	-0.065	0.190***	0.175***	-0.000	0.182***
	(0.006)	(0.046)	(0.077)	(0.048)	(0.051)	(0.105)	(0.053)
Graduate	0.028***	0.365***	0.316***	0.356***	0.340***	0.286***	0.338***
	(0.006)	(0.047)	(0.075)	(0.049)	(0.051)	(0.095)	(0.053)
Serial_Entrepreneur	0.049***	0.460***	0.511***	0.451***	0.418***	0.424***	0.421***
	(0.005)	(0.050)	(0.080)	(0.052)	(0.054)	(0.103)	(0.055)
Manager	0.043***	0.385***	0.329***	0.389***	0.366***	0.435***	0.357***
	(0.006)	(0.058)	(0.095)	(0.060)	(0.064)	(0.124)	(0.066)
Experience	-0.002***	-0.014***	-0.016***	-0.014***	-0.013***	-0.007	-0.013***
	(0.000)	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)	(0.003)
Number_Founders	0.007	0.025***	0.026***	0.025***	0.025***	0.021**	0.025***
	(0.004)	(0.008)	(0.009)	(0.008)	(0.008)	(0.010)	(0.008)
Top10_University	0.145***	0.920***	0.593***	0.962***	0.968***	0.645***	1.002***
	(0.011)	(0.054)	(0.086)	(0.055)	(0.056)	(0.102)	(0.059)
Top50_University	0.048***	0.478***	0.075	0.520***	0.481***	0.011	0.522***
	(0.008)	(0.053)	(0.092)	(0.055)	(0.058)	(0.122)	(0.060)
Top100_University	0.029***	0.298***	0.165	0.316***	0.318***	0.280**	0.321***
	(0.010)	(0.072)	(0.121)	(0.074)	(0.074)	(0.142)	(0.078)
Industry × Est. Year FE	Y	Y	Y	Y	Y	Y	Y
N	22912	21561	17832	21415	21036	15812	20934
Adj. R^2	0.089						
Pseudo R^2		0.193	0.187	0.191	0.189	0.155	0.188

Table 6. Granted Patents Filed in the US and Non-US Countries

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 in Appendix provides detailed variable definitions.

	Number of Patents (Poisson)			Indicator (OLS)		
	$All_Patent_{[t,t+5]}$	$US_Patent_{[t,t+5]}$	$Foreign_Patent_{[t,t+5]}$	$All_Patent_{[t,t+5]}$	$US_Patent_{[t,t+5]}$	$Foreign_Patent_{[t,t+5]}$
	(1)	(2)	(3)	(4)	(5)	(6)
Migrant	-0.527**	-0.435*	-0.487	-0.024***	-0.024***	-0.003
	(0.212)	(0.230)	(0.330)	(0.005)	(0.005)	(0.002)
Migrant_Native	0.777***	0.622***	0.910***	0.027***	0.026***	0.007**
	(0.217)	(0.222)	(0.342)	(0.006)	(0.006)	(0.003)
$US_Patent_{[t,t+5]}$			4.462***			0.243***
			(0.390)			(0.012)
Bachelor	-0.154	-0.123	-0.085	-0.015***	-0.014***	-0.002
	(0.155)	(0.166)	(0.206)	(0.004)	(0.004)	(0.002)
Graduate	0.497***	0.560***	0.068	0.014***	0.015***	0.000
	(0.189)	(0.205)	(0.258)	(0.004)	(0.004)	(0.002)
Serial_Entrepreneur	0.126	0.086	0.263	0.006*	0.006*	0.002
	(0.177)	(0.190)	(0.267)	(0.004)	(0.004)	(0.002)
Manager	0.209	0.168	0.285	0.006	0.005	0.002
	(0.138)	(0.135)	(0.284)	(0.004)	(0.004)	(0.002)
Experience	0.035***	0.037***	0.006	0.002***	0.002***	0.000
	(0.006)	(0.006)	(0.010)	(0.000)	(0.000)	(0.000)
Top10_University	0.639***	0.668***	0.093	0.065***	0.064***	0.006
	(0.177)	(0.166)	(0.217)	(0.009)	(0.009)	(0.004)
Top50_University	0.051	0.100	-0.440*	0.019***	0.019***	0.001
	(0.151)	(0.168)	(0.230)	(0.006)	(0.006)	(0.003)
Top100_University	0.084	-0.011	0.395	0.006	0.003	0.001
	(0.187)	(0.184)	(0.333)	(0.007)	(0.006)	(0.004)
Number_Founders	-0.068	-0.054	-0.136	-0.001	-0.001	-0.000
	(0.088)	(0.078)	(0.155)	(0.001)	(0.001)	(0.000)
Industry × Est. Year FE	Y	Y	Y	Y	Y	Y
N	19262	19090	10817	22912	22912	22912
Pseudo R^2	0.338	0.310	0.653			
Adj. R^2				0.114	0.103	0.295

Table 7. Heterogeneous Effects: Labor, Investor, and Product Market Access

This table presents results examining whether better performance of migrant-founded startups, relative to native-only ones, is enhanced by better access to migrant workers from the migrant founders' home countries (Panel A), foreign VCs from their home countries (Panel B), and product market in their home countries(Panel C). *High_Emp_Share_Home_Country* in Panel A is an indicator that is equal to one if the share of migrant employees, calculated as the number of migrant workers from a given country in a given industry and state divided by total number of employees in that state and industry in a given year, from migrant founders' home country is above the median value in a given year. *High_VC_Share_Home_Country* in Panel B is an indicator that is equal to one if the share of US firms' financing deals, calculated as the number of the deals in a given industry by VCs based in a given country divided by total number of the deals in that industry in a given year, invested by VCs based in migrant founders' home country is above the median value in a given year. *High_Patent_Share_Home_Country* in Panel C is is an indicator equal to one if share of the granted patents, calculated as the number of granted patents filed in a given non-US country by the US firms in a given industry divided by total number of granted patents filed overseas by the US firms in that industry in a given year, filed in the migrant founders' home country is above the median value in a given year. These three are equal to zero for startups without migrant founders. If a startup has multiple migrant founders with different home countries, we select the country with the highest share. 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 in Appendix provides detailed variable definitions.

Panel A. Migrant Labor Access: Share of Migrants' Home Countries

	$Ln(Emp_{t+3})$	$Funded_{[t,t+3]}$	$ln(Raised_{[t,t+3]})$	$Acq_{[t,t+5]}$	$IPO_{[t,t+10]}$
	(1)	(2)	(3)	(4)	(5)
Migrant	0.206***	0.040***	0.068**	-0.016***	0.001
	(0.023)	(0.010)	(0.034)	(0.004)	(0.002)
High_Emp_Share_Home_Country	0.055**	0.059***	0.284***	0.028***	0.005*
	(0.027)	(0.012)	(0.044)	(0.006)	(0.003)
Controls	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y
N	22912	22912	22912	22912	22912
Adj. R^2	0.053	0.137	0.130	0.017	0.052

Panel B. Foreign VC Access

	$Ln(Emp_{t+3})$	$Funded_{[t,t+3]}$	$ln(Raised_{[t,t+3]})$	$Acq_{[t,t+5]}$	$IPO_{[t,t+10]}$
	(1)	(2)	(3)	(4)	(5)
Migrant	0.196***	0.050***	0.104***	-0.006*	0.002
	(0.023)	(0.008)	(0.031)	(0.004)	(0.002)
High_VC_Share_Home_Country	0.097***	0.051***	0.277***	0.014**	0.006**
	(0.034)	(0.012)	(0.048)	(0.006)	(0.003)
Controls	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y
N	22912	22912	22912	22912	22912
Adj. R^2	0.053	0.137	0.130	0.016	0.052

Panel C. Overseas Market: Patent Share of Migrants' Home Countries

	$Ln(Emp_{t+3})$	$Funded_{[t,t+3]}$	$ln(Raised_{[t,t+3]})$	$Acq_{[t,t+5]}$	$IPO_{[t,t+10]}$
	(1)	(2)	(3)	(4)	(5)
Migrant	0.203***	0.065***	0.170***	-0.003	0.001
	(0.021)	(0.008)	(0.028)	(0.003)	(0.002)
High_Patent_Share_Home_Country	0.014	0.151	1.460**	0.148*	0.251***
	(0.449)	(0.177)	(0.687)	(0.089)	(0.084)
Controls	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y
N	22912	22912	22912	22912	22912
Adj. R^2	0.066	0.137	0.132	0.016	0.054

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

This table presents effects of migrant entrepreneurs on startup performance based on 2SLS estimates 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 in the same year, obtained the same degree, and share the same race. The sample consists of startups with at least two co-founders and one native founder and excludes startups without founders who obtained degrees from the US universities. Panel A presents summary statistics related to the IV construction. *Same_Race*, *Same_University*, *Same_Enrollment_Year*, and *Same_Degree* are indicators that are equal to one if all of the co-founders in a startup share the same race, 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. Panel B presents the first-stage estimates and the second-stage estimates for the startup performance measures. Panel C presents second-stage estimates for the the share of migrant employees, probability of getting funded by foreign VCs, and the probability of filing patents in non-US countries that are eventually granted. 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 in Appendix provides detailed variable definitions.

Panel A. Descriptive Statistics

	Cohort_Native_Share	Same_University	Same_Enrollment_Year Cond. on Same_University=1	Same_Race Cond. on Same_University=1	Same_Degree Cond. on Same_University=1
Mean	0.95	0.30	0.86	0.74	0.91

Panel B. 2SLS Results: Startup Performance

	First Stage	Second Stage				
	$Migrant_Native$	$Ln(Emp_{t+3})$	$Funded_{[t,t+3]}$	$ln(Raised_{[t,t+3]})$	$Acq_{[t,t+5]}$	$IPO_{[t,t+10]}$
	(1)	(2)	(3)	(4)	(5)	(6)
Cohort_Native_Share	-0.657***					
	(0.055)					
$\widehat{Migrant_Native}$		0.426**	0.268***	1.006***	-0.011	0.011
		(0.212)	(0.085)	(0.358)	(0.044)	(0.022)
Controls	Y	Y	Y	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y	Y	Y	Y
University FE	Y	Y	Y	Y	Y	Y
Degree×Enroll. Year FE	Y	Y	Y	Y	Y	Y
N	15013	15013	15013	15013	15013	15013
Wald F	143.6					

Panel C. 2SLS Results: Migrant Labor, Foreign VC, and Overseas Patenting

	Second Stage		
	$Mig_Emp_Share_{[t,t+5]}$	$Foreign_VC_{[t,t+5]}$	$Foreign_Patent_{[t,t+5]}$
	(1)	(2)	(3)
$\widehat{Migrant_Native}$	0.624***	0.164**	0.016
	(0.067)	(0.073)	(0.031)
Controls	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y
University FE	Y	Y	Y
Degree×Enroll. Year FE	Y	Y	Y
N	15013	15013	15013

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
Exp_Finance	The number of years of finance-related work experience before establishing a startup	LinkedIn; Revelio Lab
Exp_Marketing	The number of years of marketing-related work experience before establishing a startup	LinkedIn; Revelio Lab
Exp_Operation	The number of years of operation-related work experience before establishing a startup	LinkedIn; Revelio Lab
Exp_Sales	The number of years of sales-related work experience before establishing a startup	LinkedIn; Revelio Lab
Exp_Scientist	The number of years of science-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_Only	An indicator that is equal to one if a startup is founded solely by migrant entrepreneurs.	LinkedIn
Migrant_Native	An indicator that is equal to one if a startup is founded by both migrant and native entrepreneurs.	LinkedIn
$\text{Emp}_{[t+3]}$	The number of employees (excluding founders) in three years since startup inception year.	LinkedIn
$\text{Mig_Emp_Share}_{[t,t+5]}$	The average share of migrant employees relative to all employees over the first five years since the establishment year.	LinkedIn
$\text{Tech_Emp_Share}_{[t,t+5]}$	The average share of employees with engineering- or science-related positions over the five years since the establishment year.	LinkedIn
$\text{Bach_Emp_Share}_{[t,t+5]}$	The average share of employees with Bachelor as the highest degree relative to all migrant employees over the five years since the establishment year.	LinkedIn
$\text{Grad_Emp_Share}_{[t,t+5]}$	The average share of employees with Master, MBA, or PhD as the highest degree over the five years since the establishment year.	LinkedIn
$\text{Raised}_{[t,t+3]}$ ($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 not based in the US between year t and $t+3$ where t is the startup inception year.	Crunchbase
$\text{CVC}_{[t,t+3]}$	An indicator that is equal to one if a firm receives funding from corporate VC between year t and $t+3$ where t is the startup inception year.	Crunchbase
$\text{Top_VC_Deal}_{[t,t+3]}$	An indicator that is equal to one if a firm receives funding from top VC 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
$\text{Top_VC_Exit}_{[t,t+3]}$	An indicator that is equal to one if a firm receives funding from top VC 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
$\text{Acq}_{[t,t+10]}$	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
$\text{IPO}_{[t,t+10]}$	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
$\text{US_Patent}_{[t,t+5]}$	An indicator that is equal to one if a startup files a patent in the US between t and $t+5$, where t is the startup inception year, that is eventually granted as of 2023.	Google Patent

US_Patent$_{[t,t+10]}$	An indicator that is equal to one if a startup files a patent in the US between t and $t+10$, where t is the startup inception year, that is eventually granted as of 2023.	Google Patent
Foreign_Patent$_{[t,t+5]}$	An indicator that is equal to one if a startup files a patent outside of the US between t and $t+5$, where t is the startup inception year, that is eventually granted as of 2023.	Google Patent
Foreign_Patent$_{[t,t+10]}$	An indicator that is equal to one if a startup files a patent outside of the US between t and $t+10$, where t is the startup inception year, that is eventually granted as of 2023.	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

Table A2. 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 in Appendix 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	16.31	104.32	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	1.40	6.58	0.00	0.00	0.00	0.00	31.00
$Foreign_Top_VC_Deal_{[t,t+3]}$	66576	0.14	1.08	0.00	0.00	0.00	0.00	4.00
$Domestic_Top_VC_Deal_{[t,t+3]}$	66576	1.25	6.03	0.00	0.00	0.00	0.00	28.00
$All_Top_VC_Exit_{[t,t+3]}$	66576	0.96	4.84	0.00	0.00	0.00	0.00	24.00
$Foreign_Top_VC_Exit_{[t,t+3]}$	66576	0.07	0.71	0.00	0.00	0.00	0.00	3.00
$Domestic_Top_VC_Deal_{[t,t+3]}$	66576	0.88	4.58	0.00	0.00	0.00	0.00	20.00
$Acq_{[t,t+5]}$	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
$All_Internal_Promotion_{[t,t+5]}$	66576	4.54	8.84	0.00	0.00	1.00	4.00	53.00
$Migrant_Internal_Promotion_{[t,t+5]}$	66576	1.21	3.10	0.00	0.00	0.00	1.00	19.00
$Native_Internal_Promotion_{[t,t+5]}$	66576	3.15	6.25	0.00	0.00	1.00	3.00	37.00
$All_Departure_Promotion_{[t,t+5]}$	66576	3.12	6.18	0.00	0.00	1.00	3.00	36.00
$Migrant_Departure_Promotion_{[t,t+5]}$	66576	0.88	2.32	0.00	0.00	0.00	1.00	14.00
$Native_Departure_Promotion_{[t,t+5]}$	66576	2.13	4.41	0.00	0.00	1.00	2.00	26.00

Table A3. 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 in Appendix provides detailed variable definitions.

Panel A. All Startups with No. Founders Fixed Effects

	$Ln(Emp_{t+3})$		$Funded_{[t,t+3]}$		$ln(Raised_{[t,t+3]})$		$Acq_{[t,t+5]}$		$IPO_{[t,t+10]}$	
	(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 B. Sample Conditional on Getting Funded within Three Years

	$Ln(Emp_{t+3})$		$ln(Raised_{[t,t+3]})$		$Acq_{[t,t+5]}$		$IPO_{[t,t+10]}$	
	(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 C. Poission 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 A4. Robustness Checks: 2SLS Estimates

This table presents effects of migrant entrepreneurs on startup performance based on 2SLS estimates 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 in the same year, obtained the same degree, and share the same race. The sample consists of startups with at least two co-founders and one native founder and excludes startups without founders who obtained degrees from the US universities. 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 in Appendix provides detailed variable definitions.

Panel A. OLS Estimates

	$Ln(Emp_{t+3})$	$Funded_{[t,t+3]}$	$ln(Raised_{[t,t+3]})$	$Acq_{[t,t+5]}$	$IPO_{[t,t+10]}$	$Mig_Emp_{[t,t+5]}$	$Foreign_VC_{[t,t+5]}$	$Foreign_Pat_{[t,t+5]}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Migrant_Native	0.200***	0.046***	0.179***	0.009	0.008**	0.200***	0.059***	0.117*
	(0.030)	(0.011)	(0.045)	(0.006)	(0.003)	(0.007)	(0.009)	(0.063)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y	Y	Y	Y	Y	Y
University FE	Y	Y	Y	Y	Y	Y	Y	Y
Degree×Enrol. Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	15013	15013	15013	15013	15013	15013	15013	15013
Adj. R^2	0.08	0.17	0.15	0.01	0.05	0.18	0.08	0.16

Panel B. First Stage of 2SLS with Alternative Fixed Effects

	Migrant_Native				
	(1)	(2)	(3)	(4)	(5)
Cohort_Native_Share	-0.704***	-0.636***	-0.577***	-0.657***	-0.590***
	(0.044)	(0.054)	(0.063)	(0.055)	(0.071)
Controls	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y
University FE	N	Y	N	Y	N
Degree FE	N	Y	N	N	Y
Enrollment Year FE	N	Y	Y	N	N
University × Degree FE	N	N	Y	N	N
Degree × Enrollment Year FE	N	N	N	Y	N
University × Enrollment Year FE	N	N	N	N	Y
N	15555	15022	14453	15013	9993
Wald F	259.4	139.2	83.1	143.6	68.5
Partial R^2	0.023	0.014	0.009	0.014	0.013

Panel C. Second Stage with Alternative Fixed Effects I

	$Ln(Emp_{t+3})$	$Funded_{[t,t+3]}$	$ln(Raised_{[t,t+3]})$	$Acq_{[t,t+5]}$	$IPO_{[t,t+10]}$	$Mig_Emp_{[t,t+5]}$	$Foreign_VC_{[t,t+5]}$	$Foreign_Pat_{[t,t+5]}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Migrant_Native}$	0.416**	0.480***	1.396***	0.055	0.002	0.584***	0.341***	0.005
	(0.171)	(0.069)	(0.293)	(0.035)	(0.017)	(0.044)	(0.060)	(0.021)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	15555	15555	15555	15555	15555	15555	15555	15555

Panel D. Second Stage with Alternative Fixed Effects II

	$Ln(Emp_{t+3})$	$Funded_{[t,t+3]}$	$ln(Raised_{[t,t+3]})$	$Acq_{[t,t+5]}$	$IPO_{[t,t+10]}$	$Mig_Emp_{[t,t+5]}$	$Foreign_VC_{[t,t+5]}$	$Foreign_Pat_{[t,t+5]}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Migrant_Native}$	0.446**	0.274***	1.055***	-0.005	-0.001	0.602***	0.177**	-0.000
	(0.216)	(0.086)	(0.372)	(0.047)	(0.023)	(0.063)	(0.073)	(0.032)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y	Y	Y	Y	Y	Y
University FE	Y	Y	Y	Y	Y	Y	Y	Y
Degree FE	Y	Y	Y	Y	Y	Y	Y	Y
Enrollment Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	15022	15022	15022	15022	15022	15022	15022	15022

Panel E. Second Stage with Alternative Fixed Effects III

	$Ln(Emp_{t+3})$	$Funded_{[t,t+3]}$	$ln(Raised_{[t,t+3]})$	$Acq_{[t,t+5]}$	$IPO_{[t,t+10]}$	$Mig_Emp_{[t,t+5]}$	$Foreign_VC_{[t,t+5]}$	$Foreign_Pat_{[t,t+5]}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Migrant_Native}$	0.638**	0.344***	1.231**	0.000	-0.025	0.668***	0.226***	-0.048
	(0.279)	(0.110)	(0.492)	(0.060)	(0.030)	(0.080)	(0.087)	(0.043)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Enrollment Year FE	Y	Y	Y	Y	Y	Y	Y	Y
University × Degree FE	Y	Y	Y	Y	Y	Y	Y	Y
N	14453	14453	14453	14453	14453	14453	14453	14453

Panel F. Second Stage with Alternative Fixed Effects IV

	$Ln(Emp_{t+3})$	$Funded_{[t,t+3]}$	$ln(Raised_{[t,t+3]})$	$Acq_{[t,t+5]}$	$IPO_{[t,t+10]}$	$Mig_Emp_{[t,t+5]}$	$Foreign_VC_{[t,t+5]}$	$Foreign_Pat_{[t,t+5]}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Migrant_Native}$	0.619*	0.434***	1.477***	0.101	-0.005	0.633***	0.262**	0.038
	(0.319)	(0.132)	(0.563)	(0.079)	(0.032)	(0.086)	(0.116)	(0.044)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Degree FE	Y	Y	Y	Y	Y	Y	Y	Y
University×Enroll. Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	9993	9993	9993	9993	9993	9993	9993	9993

Internet Appendix

Table IA.1: Lowest 20 *Cohort_Native_Share* in 2010

University	Degree	Race	Cohort_Native_Share
University Of Atlanta	MBA	White	0.13
Hult International Business School	MBA	Asian	0.14
Tulane University	MBA	Hispanic	0.15
Columbia Southern University	MBA	Asian	0.17
Penn State University	Doctor	Asian	0.18
Hult International Business School	MBA	Hispanic	0.18
North Carolina State University	Doctor	Asian	0.19
University Of Delaware	Doctor	Asian	0.2
Auburn University	Master	Asian	0.21
Hult International Business School	Master	Hispanic	0.22
Clark University	Master	Asian	0.22
Hult International Business School	MBA	White	0.24
Indiana University Bloomington	Doctor	Asian	0.25
Lehigh University	Master	Asian	0.25
Washington University In St. Louis	MBA	Asian	0.25
University Of Arizona	MBA	Asian	0.25
Oklahoma State University	Master	Asian	0.26
Methodist University	MBA	Asian	0.26
University Of Nebraska Lincoln	Doctor	Asian	0.26
Purdue University	Doctor	Asian	0.27