

# Native-Immigrant Entrepreneurial Synergies

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## Motivation

- Innovation and startups are at the heart of economic growth.
- Immigrants are more entrepreneurial (Kerr and Kerr 2016; Azoulay et al. 2022) and innovative (Bernstein et al. 2022)).
  - For startups founded from 2000 to 2022 in the US, 23% have at least one migrant founder.
  - Three top global public companies and four leading U.S. private firms had immigrant founders.

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# 65% Of Top AI Companies Have Immigrant Founders

By [Stuart Anderson](#), Senior Contributor. Stuart Anderson writes about immigr...

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## Key questions

- Are migrant-founded startups more successful?
- Immigrant entrepreneurs often do not form new companies in isolation
  - For startups with at least one immigrant founder, 42% are immigrant-native founding teams.
  - Google: Sergey Brin (immigrant) and Larry Page (native)
  - Nvidia: Jensen Huang (immigrant), Chris Malachowsky (native), and Curtis Priem (native)
  - Tesla: Martin Eberhard (native), Elon Musk (immigrant), and Marc Tarpenning (native)
- Do immigrants facilitate the entrepreneurial success of native founders? Vice versa?
- What makes immigrant-native team special?
- Is it just selection?

# This Paper

**Data:** Crunchbase (firm level) + LinkedIn (individual level) + Patents

**Finding:** Native-immigrant startups outperform native-only and immigrant-only firms.

- 20-50% larger employment, 20-100% more funding and 10-50% more successful exits.

**Mechanisms:** Native and immigrant networks facilitate access to labor, financing, and consumers. Native-immigrant teams benefit by leveraging the strengths and opportunities from both groups.

- Synergies are stronger when co-founders' home countries play a key role in labor, financing, or market access.

**IV strategy:** using native classmate share rules out pure selection.

**Implications:** It's not just immigration policy—collaborative environments, such as diverse universities, which allow for immigrant-native interactions are an engine of innovation and successful new firm creation

- Entrepreneurial success is tied to the labor, capital, and product markets founders have access to through their networks

# Related Literature

- ① Disproportionate share of immigrants in
  - Entrepreneurship and startups: Kerr (2013), Kerr and Kerr (2016), Azoulay et al. (2022) , Fairlie and Lofstrom (2015), Chodavadia et al. (2024)
  - Innovation and patent productivity: Hunt and Gauthier-Loiselle (2010), Hunt (2011), Bernstein et al. (2022)

► Native-immigrant startups outperform those founded solely by either group.
- ② Ethnic ties and social networks
  - Ethnic networks in technology diffusion: Saxenian (2002), Kerr (2008)
  - Ethnic ties and venture capital: Hegde and Tumlinson (2014), Balachandran and Hernandez (2021), Eghbali, Wallskog, and Yi (2024)

► Native-immigrant teams expand access to labor, capital, and product markets, leading to better outcomes.
- ③ Team diversity and performance
  - Positive correlation between diversity and productivity: Freeman and Huang (2015), Gompers, Mukharlyamov, and Xuan (2016), Lu, Naik, and Teo (2024)
  - Negative outcomes in randomly assigned teams: Hjort (2014), Lyons (2017), Calder-Wang, Gompers, and Huang (2021)

► Consistent with endogenous team formation literature, but not driven by selection.

## Data Sources

- Firm-level information: Crunchbase
  - Considered as "the premier data asset on the tech/startup world" (Dalle, Den Besten, and Menon 2017)
  - Cover over 1.2 million companies in the United States
  - Comprehensive startup data: funding history, investors, acquisition, and IPO status.
  - Crunchbase's key advantage: coverage includes non-VC-backed startups
- Individual-level information: LinkedIn profiles collected by Revelio Labs
  - LinkedIn covers over 80% of white-collar US workers (Tambe 2014)
  - Identify entrepreneurs with LinkedIn job titles: "founder", "co-founder", or "cofounder"
  - Home country: first country listed in LinkedIn profile (education or job positions)
- Individual characteristics are constructed based on resume and Revelio Lab's text classification algorithm
  - Education: degree and university ranking
  - Job category: sales, finance, engineer, etc.
  - Experience: number of years of all work experience or in different job categories
  - Seniority: seven levels with four or above being managerial positions

## Data Linkage

- Linking startups to founders and employees: company LinkedIn URL
- Company LinkedIn URLs are unique, consistent identifiers across databases.
- 70% of US-based firms in the LinkedIn database have profile URLs
- 85% of US-based firms in Crunchbase provide LinkedIn profile URLs
- LinkedIn-Crunchbase sample: 135k entrepreneurs founding 91k U.S. startups (2000-2022).

The screenshot shows the LinkedIn company profile for OpenAI. At the top, there's a navigation bar with the LinkedIn logo, a search bar, and links for Home, My Network, Jobs, Messaging, and Notifications (with a red notification badge showing 7). Below the bar is a large, colorful abstract painting of a landscape. Overlaid on the left side of the painting is a white square containing the OpenAI logo, which is a stylized black knot or swirl. Below the image, the company name "OpenAI" is displayed in bold black text, followed by a blue checkmark icon indicating verification. A subtitle reads "Creating safe AGI that benefits all of humanity." Below that, it says "Research Services · San Francisco, CA · 6M followers · 201-500 employees". At the bottom of the profile, there are buttons for "+ Follow", "Visit website", and a three-dot menu. A horizontal navigation bar at the very bottom includes links for Home, About, Posts, Jobs, Life, and People.

## Sample

- Focus on 53,740 entrepreneurs co-founding 22,967 U.S. startups (2000-2017):
  - Excludes single founders, as promising projects attract co-founders
  - Sample ends in 2017 to allow 5+ years for outcomes (acquisition, IPO, patenting).

	N(Migrant)	N(Native)	$\mu$ (Migrant)	$\mu$ (Native)	Migrant - Native
Bachelor	12872	40868	0.23	0.32	-0.091***
Graduate	12872	40868	0.42	0.26	0.153***
Top10_University	12872	40868	0.04	0.06	-0.017***
Top50_University	12872	40868	0.07	0.07	-0.003
Top100_University	12872	40868	0.04	0.03	0.004**
Male	12872	40868	0.70	0.76	-0.066***
Serial_Entrepreneur	12872	40868	0.41	0.39	0.012**
Manager	12872	40868	0.51	0.49	0.011**
Experience	12872	40868	9.24	9.40	-0.164**
Observations	53740				

- Migrant co-founders are more likely to have graduate degrees, less experience overall, but more in engineering and science, and less in finance and marketing.

► More Details on Experience

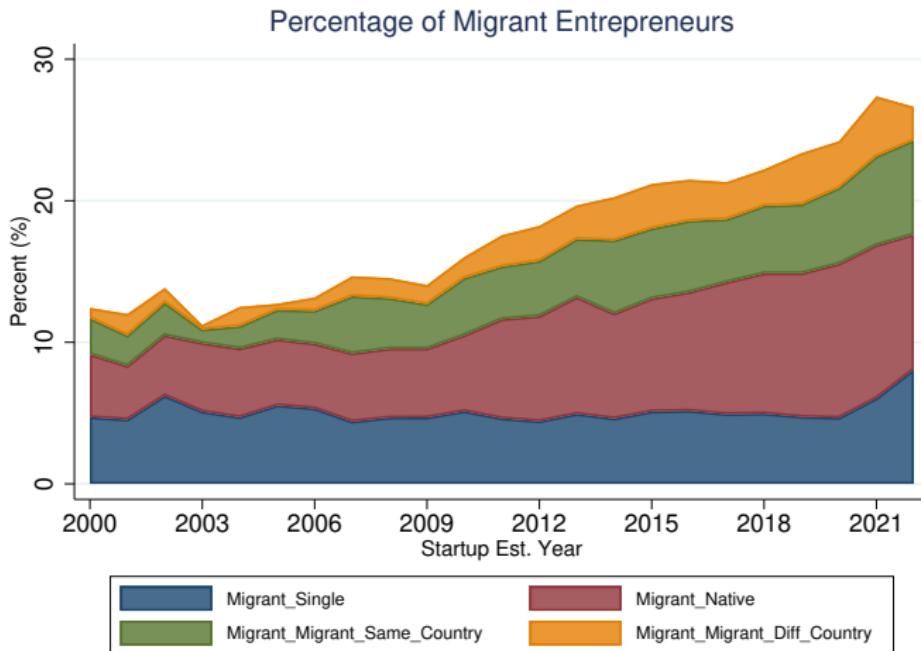
## Firm-level Summary Statistics

	Mean	P25	P50	P75	P99
<i>Migrant</i>	0.33	0.00	0.00	1.00	1.00
<i>Migrant_Native</i>	0.22	0.00	0.00	0.00	1.00
<i>Emp_{t+3}</i>	26.10	3.00	6.00	14.00	149.00
<i>Mig_Emp_Share_{[t,t+5]}</i>	0.30	0.02	0.17	0.50	1.00
<i>Raised_{[t,t+3]} (\\$MM)</i>	38.37	0.00	0.00	3.07	855.00
<i>Funded_{[t,t+3]}</i>	0.36	0.00	0.00	1.00	1.00
<i>Foreign_VC_{[t,t+3]}</i>	0.18	0.00	0.00	0.00	1.00
<i>Acq_{[t,t+5]}</i>	0.06	0.00	0.00	0.00	1.00
<i>IPO_{[t,t+10]}</i>	0.01	0.00	0.00	0.00	1.00
<i>Number_Founders</i>	2.51	2.00	2.00	3.00	6.00
Observations	22967				

- Note the significance of migrant employees and foreign VCs for startups.

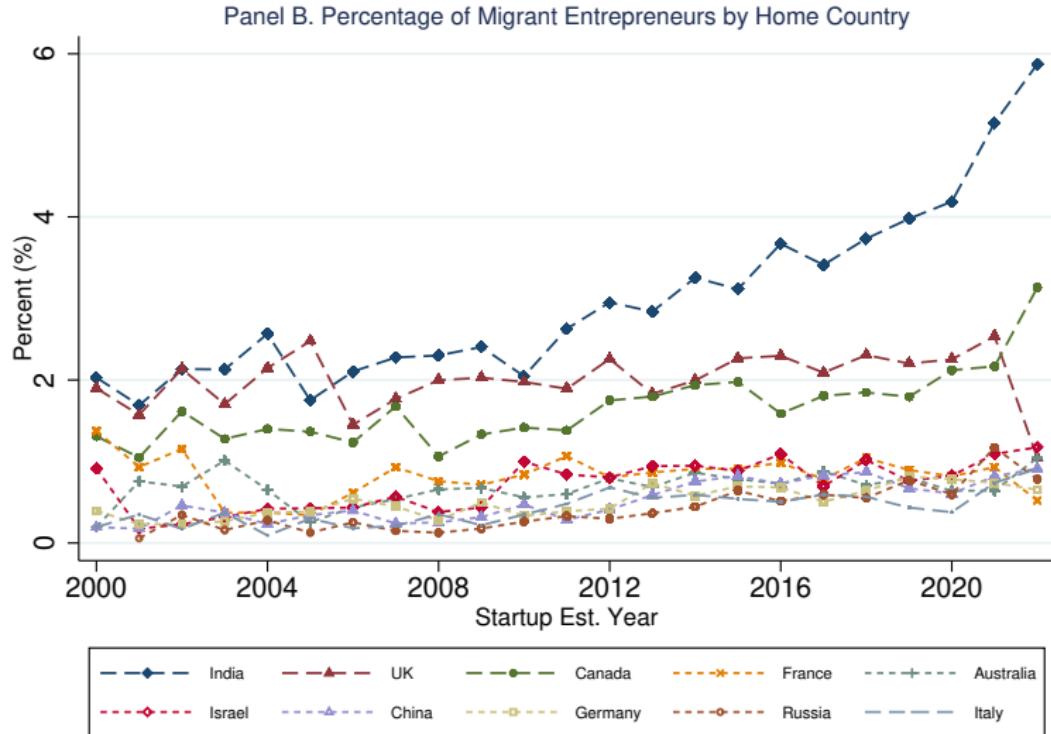
▶ Firm-Level Summary Stats: All Variables

# Rise of Migrant Entrepreneurs



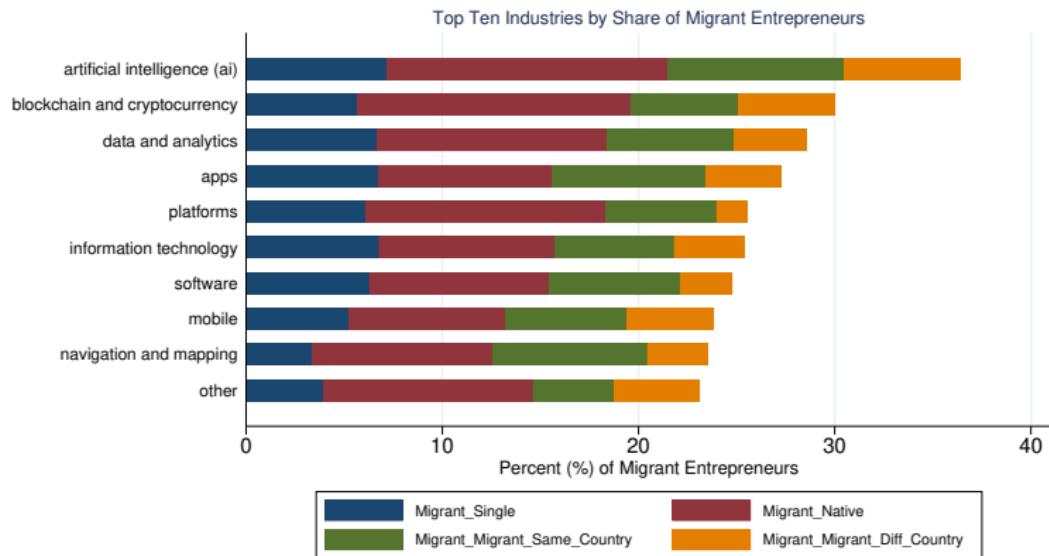
▶ CoFound Type Percentages

# Trends of Migrant Entrepreneurs by Country of Origin



▶ CoFound Type By Country

# Top Ten Industries by Percentage of Migrant Entrepreneurs



► Top 10 By Number

## Univariate Analyses

	Mig- Only	Native- Only	Mig- Native	Mig-Native - Mig-Only	Mig-Native - Native-Only
$\ln(Emp_{t+3})$	1.92	1.75	2.09	0.17***	0.33***
$Funded_{[t,t+3]}$	0.42	0.32	0.46	0.03**	0.13***
$\ln(Raised_{[t,t+3]})$	1.03	0.88	1.37	0.35***	0.49***
$Acq_{[t,t+5]}$	0.04	0.05	0.07	0.03***	0.02***
$IPO_{[t,t+10]}$	0.01	0.01	0.02	0.01***	0.01***
<i>Graduate</i>	0.65	0.42	0.62	-0.03*	0.20***
<i>Serial Entrepreneur</i>	0.66	0.63	0.72	0.06***	0.09***
<i>Manager</i>	0.74	0.72	0.79	0.04***	0.06***
<i>Experience</i>	12.06	12.83	14.21	2.15***	1.38***
<i>Top10_University</i>	0.06	0.10	0.14	0.08***	0.04***
<i>Top50_University</i>	0.11	0.13	0.17	0.06***	0.04***

- Native-migrant startups demonstrate superior outcomes, but they also had more educated and experienced founders.

# Superior Performance of Migrant-Native Startups

We start with the following firm-level OLS regression:

$$\text{Performance}_{i,[t,t+\tau]} = \beta_1 \text{Migrant}_{i,t} + \beta_2 \text{Migrant\_Native}_{i,t} + \Gamma' X_{i,t} + \alpha_{j,t} + \epsilon_{i,t}$$

- Performance measures:  $\ln(\text{Emp}_{t+3})$ ,  $\text{Funded}_{[t,t+3]}$ ,  $\ln(\text{Raised}_{[t,t+3]})$ ,  $\text{Acq}_{[t,t+5]}$ ,  $\text{IPO}_{[t,t+10]}$
- $\text{Migrant}_{i,t}$ : equal to one if a startup founded by at least one migrant founder
- $\text{Migrant\_Native}_{i,t}$ : equal to one if a startup co-founded by both migrant and native founders
- $\beta_1$  (without  $\beta_2$ ): startups with at least one migrant vs. native-only
- $\beta_1$  (with  $\beta_2$ ): migrant-only vs. native-only
- $\beta_2$ : migrant-native vs. migrant-only startups.
- $\alpha_{j,t}$ : Industry  $\times$  Inception Year fixed effects
- Control Variables: *Bachelor*, *Graduate*, *Seiral\_Entrepreneur*, *Experience*, *Manager*, *Number\_Founders*, *Top10\_University*, *Top50\_University*, *Top50\_University*

# Superior Performance of Migrant-Native Startups

	$\ln(Emp_{t+3})$		$\ln(Raised_{[t,t+3]})$	
	(1)	(2)	(3)	(4)
<i>Migrant</i>	0.203*** (0.020)	0.147*** (0.028)	0.188*** (0.027)	0.066 (0.043)
<i>Migrant_Native</i>		0.083*** (0.029)		0.180*** (0.046)
Controls	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y
N	22912	22912	22912	22912
Adj. $R^2$	0.066	0.066	0.132	0.132

# Superior Performance of Migrant-Native Startups

	$Acq_{[t,t+5]}$		$IPO_{[t,t+10]}$	
	(1)	(2)	(3)	(4)
<i>Migrant</i>	-0.002 (0.003)	-0.019*** (0.005)	0.004** (0.002)	0.000 (0.002)
<i>Migrant_Native</i>		0.025*** (0.006)		0.005* (0.003)
Controls	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y
N	22912	22912	22912	22912
Adj. $R^2$	0.016	0.017	0.052	0.052

► Including Single Founders

► Founder-Startup Level

► Funded Firms Only

► State-Year FE

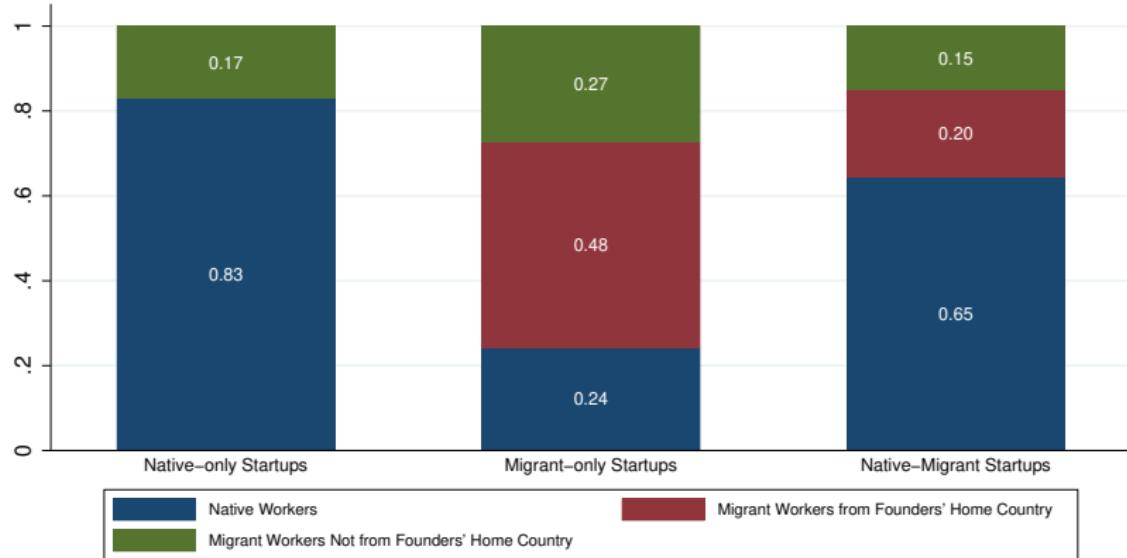
## Investigating Potential Mechanisms

We hypothesize that native-immigrant collaboration allows startups access to more sources of labor and capital and facilitates entry into more product markets

- ① Migrants facilitate access to high quality foreign labor, while natives facilitate access to high quality domestic labor. Native-migrant startups should have higher quality workers.
- ② VCs play important monitoring and networking roles. Migrants facilitate access to foreign VCs, while natives facilitate access to domestic VCs. Native-migrant startups should work with more successful VCs.
- ③ Product market access is often secured through patents. Migrants should facilitate access to foreign product markets through foreign patents, while natives should facilitate access to domestic product markets through domestic patents.

# Employees' Country of Origin

Panel A. Migrant Employees and Founders' Home Country



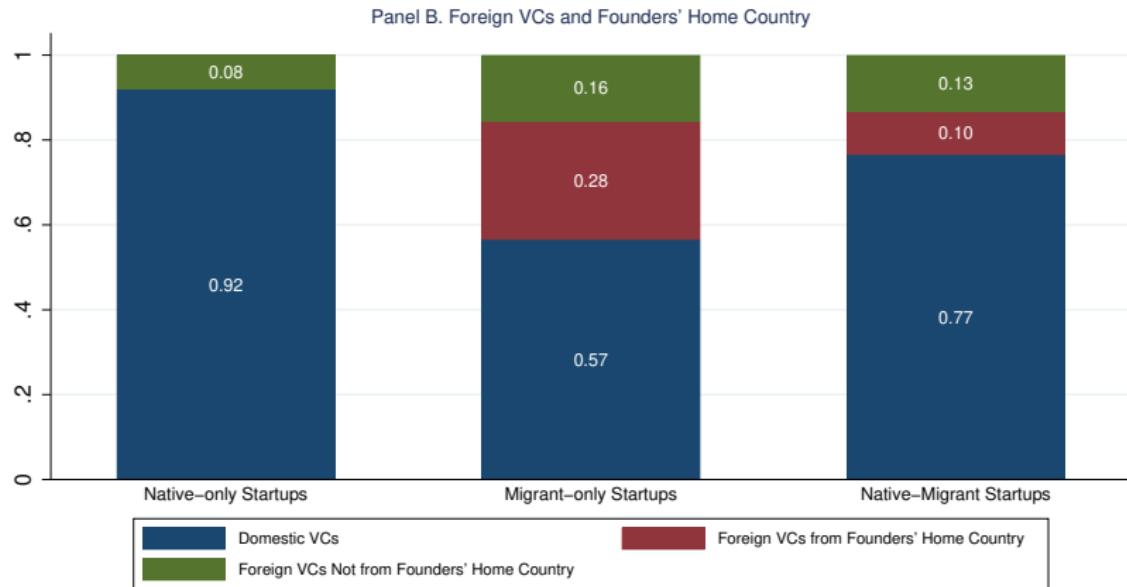
# Inspecting Mechanisms I: Better Pool of Labor

	<i>Mig_Emp_Share<sub>[t,t+5]</sub></i>	Number of Workers Internally Promoted		
		<i>All<sub>[t,t+5]</sub></i>	<i>Migrant<sub>[t,t+5]</sub></i>	<i>Native<sub>[t,t+5]</sub></i>
		(1)	(2)	(4)
<i>Migrant</i>	0.552*** (0.007)	0.145*** (0.038)	1.284*** (0.038)	-0.920*** (0.057)
<i>Migrant_Native</i>	-0.278*** (0.008)	0.132*** (0.038)	-0.280*** (0.037)	0.827*** (0.056)
Controls	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y
N	22912	22908	22769	22871
Adj. <i>R</i> <sup>2</sup>	0.360			
Pseudo <i>R</i> <sup>2</sup>		0.110	0.191	0.112

► Externally Promoted

► Employees by Country of Origin

# Foreign VCs' Country of Origin



## Inspecting Mechanisms II: Better Funding

	<i>Foreign VC</i> <sub>[t, t+3]</sub>	Number of Top VCs by Deals		
		<i>All</i> <sub>[t, t+3]</sub>	<i>Foreign</i> <sub>[t, t+3]</sub>	<i>Domestic</i> <sub>[t, t+3]</sub>
		(1)	(2)	(4)
<i>Migrant</i>	0.123*** (0.010)	-0.043 (0.066)	1.533*** (0.094)	-0.361*** (0.071)
<i>Migrant_Native</i>	-0.037*** (0.012)	0.296*** (0.070)	-0.344*** (0.085)	0.501*** (0.077)
Controls	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y
N	22912	21561	17832	21415
Adj. <i>R</i> <sup>2</sup>	0.089			
Pseudo <i>R</i> <sup>2</sup>		0.193	0.187	0.191

► Top VCs by Exits

► Top VCs by Country of Origin

## Inspecting Mechanisms III: Better Product Market Access

	Indicator (OLS)		
	<i>All_Patent</i> <sub>[t,t+5]</sub>	<i>US_Patent</i> <sub>[t,t+5]</sub>	<i>Foreign_Patent</i> <sub>[t,t+5]</sub>
	(1)	(2)	(3)
<i>Migrant</i>	-0.024*** (0.005)	-0.024*** (0.005)	-0.003 (0.002)
<i>Migrant_Native</i>	0.027*** (0.006)	0.026*** (0.006)	0.007** (0.003)
<i>US_Patent</i> <sub>[t,t+5]</sub>			0.243*** (0.012)
Controls	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y
N	22912	22912	22912
Adj. <i>R</i> <sup>2</sup>	0.114	0.103	0.295

## Heterogeneity Tests

- Examine synergies in industries and states where migrant co-founders' home countries play a key role in labor, financing, or market access.
- **Labor:** share of migrant employees from migrant founders' home countries in an industry-state-year relative to all employees in that industry-state-year
- **Financing:** share of financing deals by VCs based in migrant founders' home countries in an industry-year relative to all financing deals in that industry-year
- **Product market:** share of granted patents filed in migrant founders' home countries in an industry relative to all the patents filed overseas by the US firms in that industry
- Construct indicators equal to one if the corresponding share is above the sample median for a non-US country in a given year
  - *High\_Emp\_Share\_Home\_Country* ► Labor\_CA ► Labor\_NY ► Labor\_MA
  - *High\_VC\_Share\_Home\_Country* ► VC\_industry\_country
  - *High\_Patent\_Share\_Home\_Country* ► Patent\_industry\_country

# Heterogeneity Test: Results

	$\ln(Emp_{t+3})$	$\ln(Raised_{[t,t+3]})$	$Acq_{[t,t+5]}$	$IPO_{[t,t+10]}$
<b>Panel A:</b>				
<i>Migrant</i>	0.206*** (0.023)	0.068** (0.034)	-0.016*** (0.004)	0.001 (0.002)
<i>High_Emp_Share_Home_Country</i>	0.055** (0.027)	0.284*** (0.044)	0.028*** (0.006)	0.005* (0.003)
<b>Panel B:</b>				
<i>Migrant</i>	0.196*** (0.023)	0.104*** (0.031)	-0.006* (0.004)	0.002 (0.002)
<i>High_VC_Share_Home_Country</i>	0.097*** (0.034)	0.277*** (0.048)	0.014** (0.006)	0.006** (0.003)
<b>Panel C:</b>				
<i>Migrant</i>	0.203*** (0.021)	0.170*** (0.028)	-0.003 (0.003)	0.001 (0.002)
<i>High_Patent_Share_Home_Country</i>	0.014 (0.449)	1.460** (0.687)	0.148* (0.089)	0.251*** (0.084)
Controls	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y
N	22,912			

▶ Three combined

# Native-Immigrant Synergies vs. Endogenous Selection

- Homophily preferences (McPherson, Smith-Lovin, and Cook 2001) can result in lower threshold for native-only or migrant-only startups.
  - Baseline results can be driven by selection.
- We construct IV based on the share of native students at degree-university-year level:

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

- $Native_{u,d,t}$ : the number of native students who obtained degree  $d$  at the US university  $u$  with enrollment year  $t$
- $Foreign_{u,d,t}$ : the number of international students who obtained degree  $d$  at the US university  $u$  with enrollment year  $t$
- A higher share of native students predicts a higher (lower) likelihood for migrant (native) to co-found a migrant-native startup

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

## Two-Stage Least Square

We estimate the following 2SLS regressions at **founder-startup** level:

$$\begin{aligned} Migrant\_Native_{i,j,t} &= \gamma Cohort\_Native\_Share_i + \Gamma' X_{i,j,t} + \alpha_{j,t} + Edu\ FE + \epsilon_{i,j,t} \\ Performance_{i,j,[t,t+\tau]} &= \beta \widehat{Migrant\_Native}_{i,j,t} + \Gamma' X_{i,j,t} + \alpha_{j,t} + Edu\ FE + \epsilon_{i,t} \end{aligned}$$

We estimate above equations separately for two distinct samples:

- ① Sample I: startups with at least one **native** founder
  - ② Sample II: startups with at least one **migrant** founder
- 
- $\beta$  in Sample I: migrant-native vs. native-only
  - $\beta$  in Sample II: migrant-native vs. migrant-only
  - *Edu FE*: University  $\times$  Degree fixed effects

## IV Estimates: Migrant-Native vs. Native

	First Stage			Second Stage		
	<i>Migrant_Native</i>	<i>Ln(Emp<sub>t+3</sub>)</i>	<i>Funded<sub>[t,t+3]</sub></i>	<i>ln(Raised<sub>[t,t+3]</sub>)</i>	<i>Acq<sub>[t,t+5]</sub></i>	<i>IPO<sub>[t,t+10]</sub></i>
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Cohort_Native_Share</i>	-0.761*** (0.065)					
<i>Migrant_Native</i>		0.444* (0.241)	0.355*** (0.092)	1.287*** (0.379)	0.018 (0.047)	-0.011 (0.020)
Controls	Y	Y	Y	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y	Y	Y	Y
University×Degree FE	Y	Y	Y	Y	Y	Y
N	27601	27601	27601	27601	27601	27601
Wald F	138.8					

## IV Estimates of Mechanisms: Migrant-Native vs. Native

	Second Stage		
	<i>Mig_Emp_Share<sub>[t,t+5]</sub></i>	<i>Foreign_VC<sub>[t,t+5]</sub></i>	<i>Foreign_Patent<sub>[t,t+5]</sub></i>
	(1)	(2)	(3)
<i>Migrant_Native</i>	0.430*** (0.061)	0.263*** (0.076)	0.031 (0.027)
Controls	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y
University×Degree FE	Y	Y	Y
N	27601	27601	27601

## IV Estimates: Migrant-Native vs. Migrants

	First Stage			Second Stage		
	<i>Migrant_Native</i>	<i>Ln(Emp<sub>t+3</sub>)</i>	<i>Funded<sub>[t,t+3]</sub></i>	<i>ln(Raised<sub>[t,t+3]</sub>)</i>	<i>Acq<sub>[t,t+5]</sub></i>	<i>IPO<sub>[t,t+10]</sub></i>
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Cohort_Native_Share</i>	1.063*** (0.101)					
<i>Migrant_Native</i>		0.906** (0.352)	0.155 (0.121)	1.492*** (0.558)	-0.013 (0.058)	0.083** (0.039)
Controls	Y	Y	Y	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y	Y	Y	Y
University×Degree FE	Y	Y	Y	Y	Y	Y
N	6525	6525	6525	6525	6525	6525
Wald F	110.6					

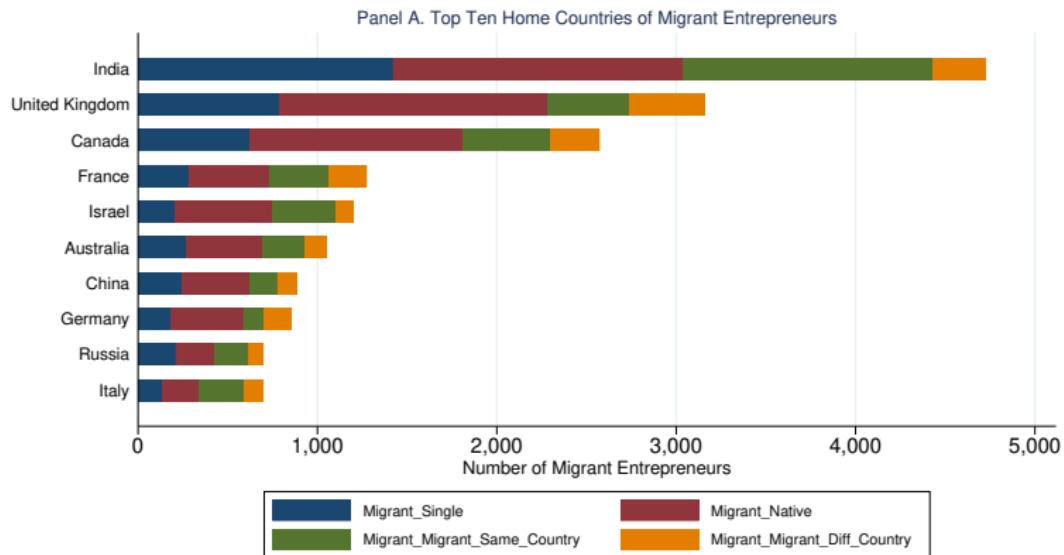
## IV Estimates of Mechanisms: Migrant-Native vs. Migrants

	Second Stage		
	<i>Mig_Emp_Share</i> <sub>[t, t+5]</sub>	<i>Foreign_VC</i> <sub>[t, t+5]</sub>	<i>Foreign_Patent</i> <sub>[t, t+5]</sub>
	(1)	(2)	(3)
<i>Migrant_Native</i>	-0.425*** (0.078)	-0.003 (0.100)	0.071** (0.034)
Controls	Y	Y	Y
Industry×Est. Year FE	Y	Y	Y
University×Degree FE	Y	Y	Y
N	6525	6525	6525

## Conclusion

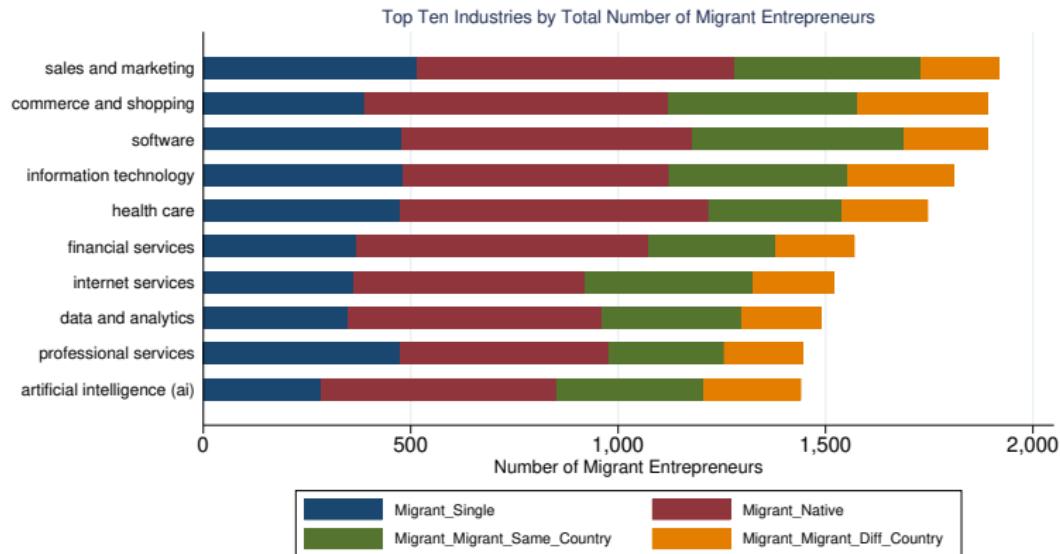
- Migrants play a disproportionate role in new firm creation in the United States. A significant fraction of migrant founders collaborate with native founders when starting a company
- Native-immigrant startups have higher employment growth, raise more capital, and have more successful exits than either native-only or migrant-only startups
- Native-immigrant startups access higher quality labor, raise capital from more successful VCs, and access a greater diversity of product markets than either native-only or migrant-only startups
- Results are robust to an IV strategy that exploits plausibly exogenous variation in the native share of graduate classmates, suggesting results are not driven purely by selection
- Immigrants are an important driver of US-based entrepreneurial activity, but it is the **collaboration** of natives and migrants that is particularly fruitful

# CoFound Type By Country



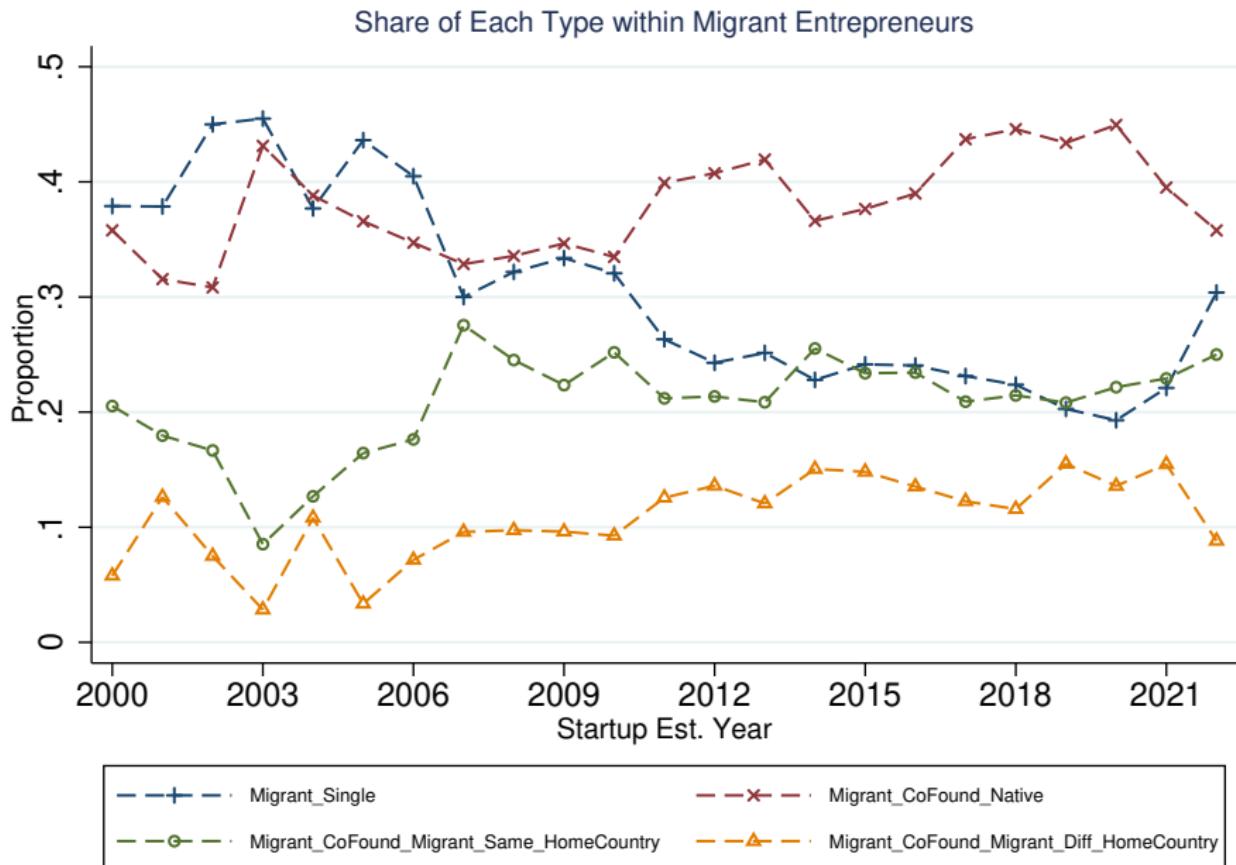
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# Top Ten Industries by Number of Migrant Entrepreneurs

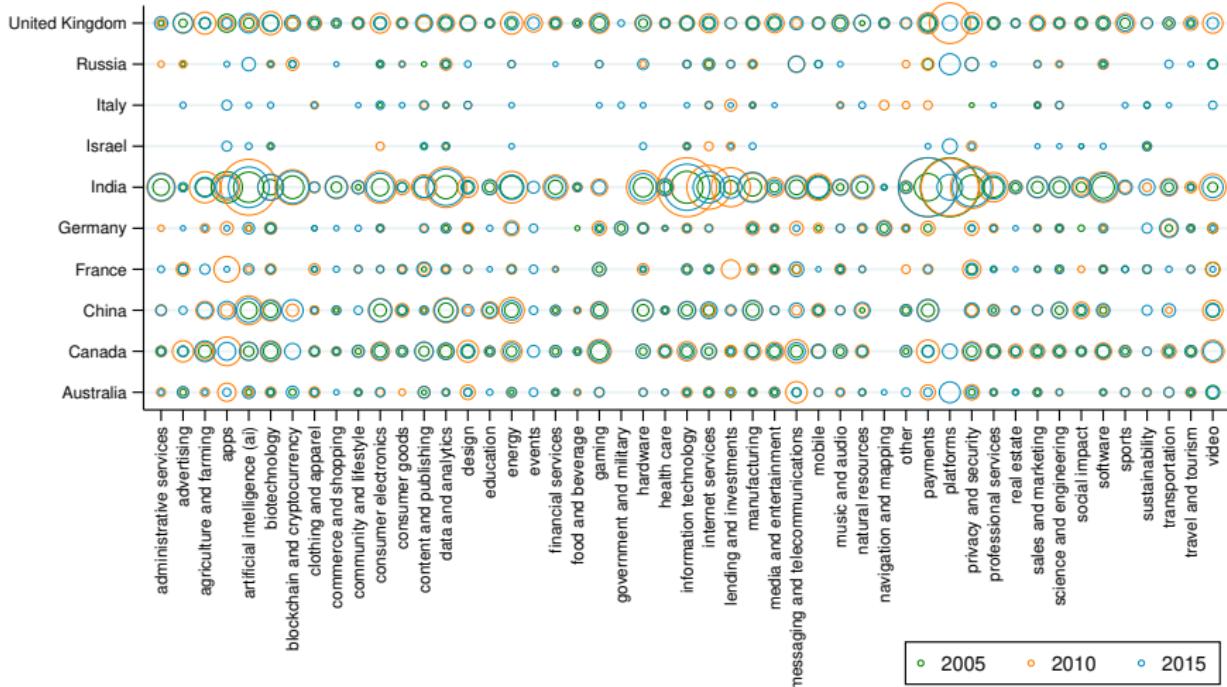


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# Rise of Migrant Entrepreneurs

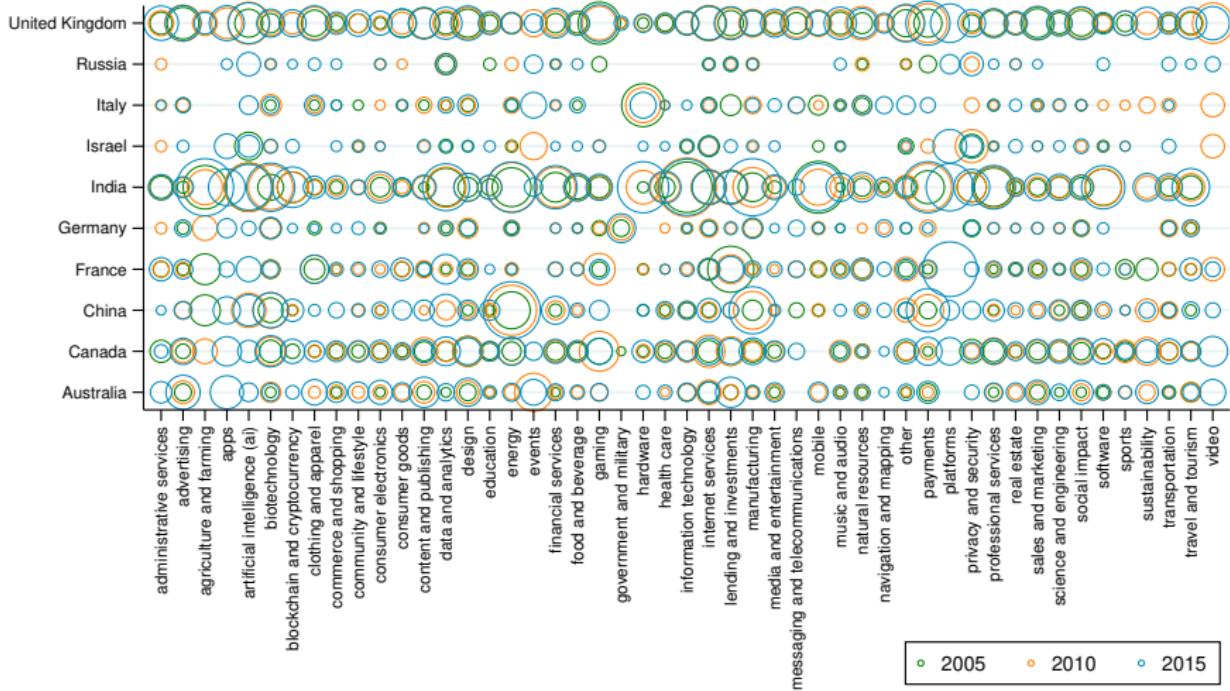


## Panel A. Migrant Labor Share in California by Industry and Country



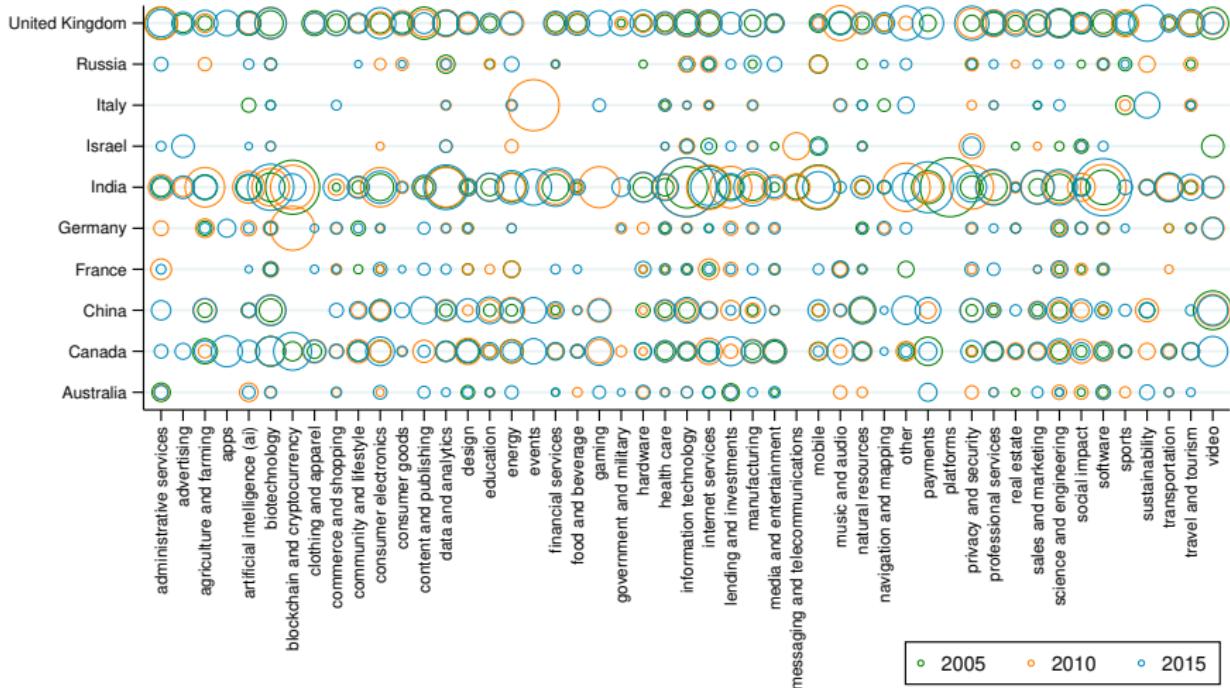
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## Panel B. Migrant Labor Share in New York State by Industry and Country



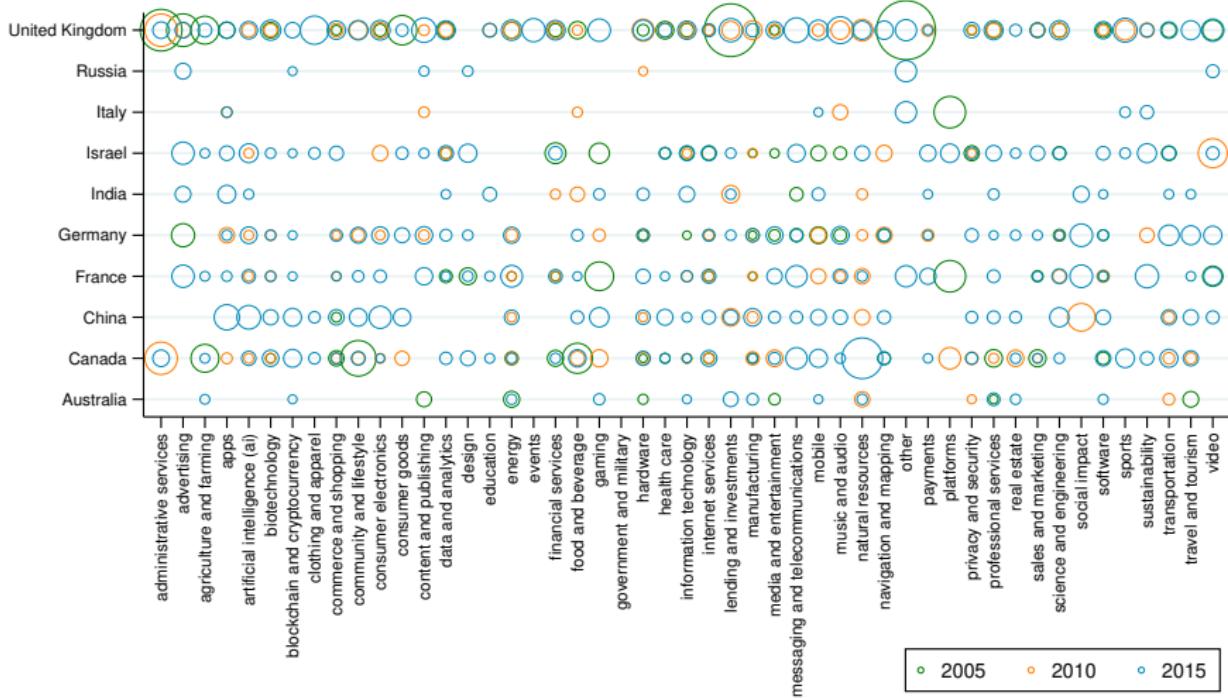
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### Panel C. Migrant Labor Share in Massachusetts by Industry and Country



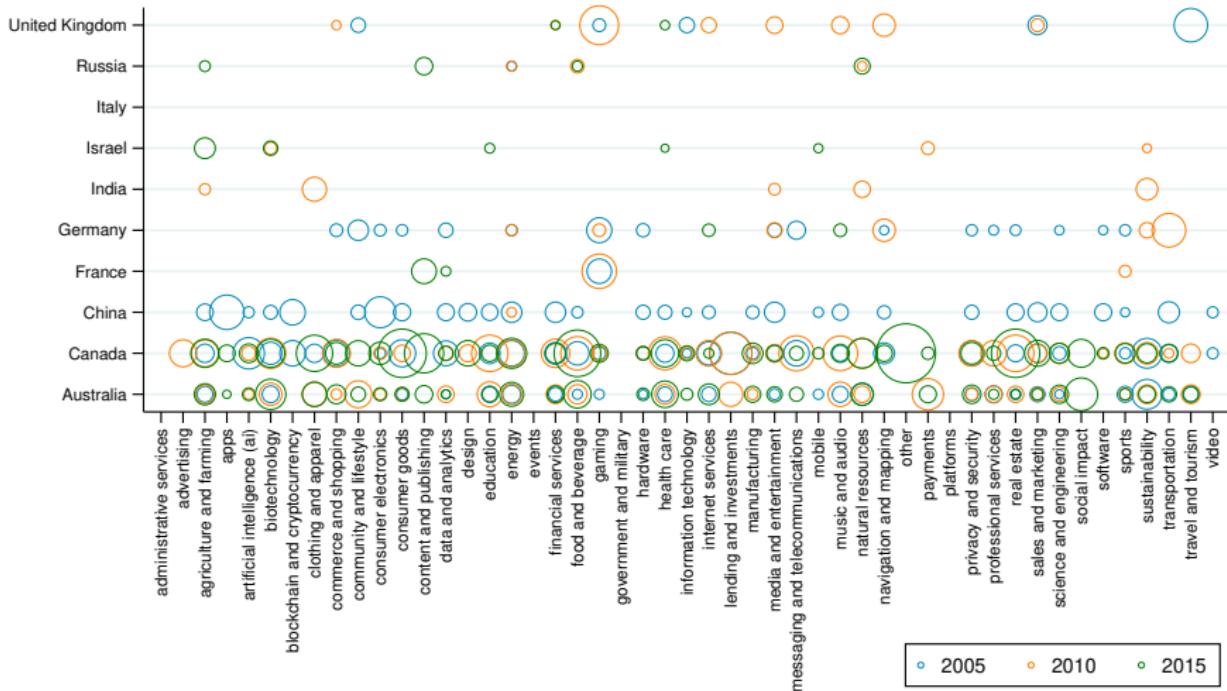
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## Foreign Investor Share by Industry and Country



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## Share of Granted Patents by Industry and Filing Country



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# Firm-Level Summary Statistics: All Variables

	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
Empt <sub>t+3</sub>	22967	26.10	637.33	1.00	3.00	6.00	14.00	149.00
Mig_Emp_Share <sub>[t,t+5]</sub>	22967	0.30	0.33	0.00	0.02	0.17	0.50	1.00
Raised <sub>[t,t+3]</sub> (\$MM)	22967	44.47	309.66	0.00	0.00	0.00	3.07	855.00
Funded <sub>[t,t+3]</sub>	22967	0.36	0.48	0.00	0.00	0.00	1.00	1.00
Foreign_VC <sub>[t,t+3]</sub>	22967	0.18	0.38	0.00	0.00	0.00	0.00	1.00
All_Top_VC_Deal <sub>[t,t+3]</sub>	22967	1.73	5.13	0.00	0.00	0.00	1.00	24.00
Foreign_Top_VC_Deal <sub>[t,t+3]</sub>	22967	0.23	1.17	0.00	0.00	0.00	0.00	5.00
Domestic_Top_VC_Deal <sub>[t,t+3]</sub>	22967	1.50	4.61	0.00	0.00	0.00	0.00	22.00
All_Top_VC_Exit <sub>[t,t+3]</sub>	22967	0.88	2.96	0.00	0.00	0.00	0.00	14.00
Foreign_Top_VC_Exit <sub>[t,t+3]</sub>	22967	0.08	0.53	0.00	0.00	0.00	0.00	2.00
Domestic_Top_VC_Deal <sub>[t,t+3]</sub>	22967	0.81	2.78	0.00	0.00	0.00	0.00	13.00
Acq <sub>[t,t+5]</sub>	22967	0.06	0.23	0.00	0.00	0.00	0.00	1.00
IPO <sub>[t,t+10]</sub>	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 <sub>[t,t+5]</sub>	22967	0.55	5.76	0.00	0.00	0.00	0.00	12.00
US_Patent <sub>[t,t+5]</sub>	22967	0.41	4.42	0.00	0.00	0.00	0.00	9.00
Foreign_Patent <sub>[t,t+5]</sub>	22967	0.14	2.09	0.00	0.00	0.00	0.00	3.00
All_Internal_Promotion <sub>[t,t+5]</sub>	22967	6.84	11.20	0.00	1.00	3.00	7.00	53.00
Migrant_Internal_Promotion <sub>[t,t+5]</sub>	22967	2.03	4.07	0.00	0.00	0.00	2.00	19.00
Native_Internal_Promotion <sub>[t,t+5]</sub>	22967	4.47	7.76	0.00	0.00	1.00	5.00	37.00
All_Departure_Promotion <sub>[t,t+5]</sub>	22967	4.56	7.60	0.00	0.00	2.00	5.00	36.00
Migrant_Departure_Promotion <sub>[t,t+5]</sub>	22967	1.42	2.98	0.00	0.00	0.00	1.00	14.00
Native_Departure_Promotion <sub>[t,t+5]</sub>	22967	2.96	5.34	0.00	0.00	1.00	3.00	26.00
Business_Business	22967	0.59	0.49	0.00	0.00	1.00	1.00	1.00
Tech_Tech	22967	0.09	0.29	0.00	0.00	0.00	0.00	1.00

# Sample

	N(Migrant)	N(Native)	$\mu$ (Migrant)	$\mu$ (Native)	Migrant - Native
<i>Exp_Engineer</i>	12872	40868	2.83	1.88	0.949***
<i>Exp_Finance</i>	12872	40868	0.51	0.85	-0.340***
<i>Exp_Marketing</i>	12872	40868	1.43	1.71	-0.273***
<i>Exp_Operation</i>	12872	40868	0.99	1.02	-0.038
<i>Exp_Sales</i>	12872	40868	2.47	2.68	-0.215***
<i>Exp_Scientist</i>	12872	40868	0.77	0.62	0.152***
Observations	53740				

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## Baseline Results with State×Year Fe

	$\ln(Emp_{t+3})$	$Funded_{[t,t+3]}$	$\ln(Raised_{[t,t+3]})$	$Acq_{[t,t+5]}$	$IPO_{[t,t+10]}$
	(1)	(2)	(3)	(4)	(5)
<i>Migrant</i>	0.106*** (0.034)	0.054*** (0.014)	0.050 (0.056)	-0.017* (0.009)	-0.002 (0.003)
<i>Migrant_Native</i>	0.075** (0.036)	-0.003 (0.015)	0.116** (0.057)	0.020** (0.010)	0.007** (0.003)
Controls	Y	Y	Y	Y	Y
Industry × Est.Year FE	Y	Y	Y	Y	Y
State × Est.Year FE	Y	Y	Y	Y	Y
N	21132	21132	21132	21132	21132
Adj. $R^2$	0.069	0.178	0.166	0.049	0.047

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# Superior Performance of Migrant-Native Startups - Including Firms with One Founder

	$\ln(Emp_{t+3})$ (2)	$Funded_{[t,t+3]}$ (4)	$\ln(Raised_{[t,t+3]})$ (6)	$Acq_{[t,t+5]}$ (8)	$IPO_{[t,t+10]}$ (10)
<i>Migrant</i>	0.142*** (0.016)	0.047*** (0.006)	0.050*** (0.018)	-0.009*** (0.002)	-0.000 (0.001)
<i>Migrant_Native</i>	0.051** (0.021)	0.010 (0.010)	0.148*** (0.032)	0.015*** (0.004)	0.005* (0.003)
Controls	Y	Y	Y	Y	Y
No. Founder FE	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y
N	66549	66549	66549	66549	66549
Adj. $R^2$	0.078	0.166	0.177	0.021	0.043

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# Superior Performance of Migrant-Native Startups - Founder-Startup Level

	$\ln(Emp_{t+3})$		$\ln(Raised_{[t,t+3]})$		$Acq_{[t,t+5]}$	
	(1)	(2)	(5)	(6)	(7)	(8)
<i>Migrant</i>	0.132*** (0.047)	0.074 (0.049)	0.210** (0.082)	-0.087 (0.081)	-0.022*** (0.008)	-0.030*** (0.009)
<i>Migrant_Native</i>	0.187*** (0.050)	0.197*** (0.049)	0.255*** (0.088)	0.397*** (0.086)	0.038*** (0.010)	0.040*** (0.011)
<i>Serial_Entrepreneur</i>	0.115*** (0.016)	0.099*** (0.016)	0.177*** (0.026)	0.139*** (0.026)	0.009*** (0.003)	0.007** (0.003)
<i>Controls</i>	Y	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y	Y
University FE	N	Y	N	Y	N	Y
Degree FE	N	Y	N	Y	N	Y
N	32223	31634	32223	31634	32223	31634
Adj. $R^2$	0.122	0.150	0.116	0.166	0.050	0.048

▶ Return

# Superior Performance of Migrant-Native Startups Conditional On Receiving Funding

	$\ln(Emp_{t+3})$		$\ln(Raised_{[t,t+3]})$		$Acq_{[t,t+5]}$	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Migrant</i>	0.119*** (0.029)	-0.013 (0.043)	0.151*** (0.045)	-0.123* (0.072)	-0.009 (0.008)	-0.037*** (0.010)
<i>Migrant_Native</i>		0.187*** (0.041)		0.389*** (0.073)		0.038*** (0.011)
Controls	Y	Y	Y	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y	Y	Y	Y
N	7192	7192	7192	7192	7192	7192
Adj. $R^2$	0.048	0.050	0.116	0.120	0.014	0.015

► Return

# Heterogeneity

	$\ln(Emp_{t+3})$	$Funded_{[t,t+3]}$	$\ln(Raised_{[t,t+3]})$	$Acq_{[t,t+5]}$	$IPO_{[t,t+10]}$
	(1)	(2)	(3)	(4)	(5)
<i>Migrant</i>	0.155*** (0.026)	0.027*** (0.010)	-0.018 (0.035)	-0.019*** (0.004)	-0.002 (0.002)
<i>High_Emp_Share_Home_Country</i>	0.048* (0.027)	0.052*** (0.012)	0.242*** (0.046)	0.027*** (0.006)	0.003 (0.003)
<i>High_VC_Share_Home_Country</i>	0.069** (0.034)	0.038*** (0.013)	0.203*** (0.051)	0.007 (0.006)	0.002 (0.003)
<i>High_Patent_Share_Home_Country</i>	-0.312 (0.449)	-0.084 (0.178)	0.289 (0.696)	0.070 (0.092)	0.237*** (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	0.139	0.134	0.017	0.054

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## Inspecting Mechanisms I: Better Pool of Labor

	Number of Workers Promoted After Departure		
	$All_{[t,t+5]}$	$Migrant_{[t,t+5]}$	$Native_{[t,t+5]}$
	(1)	(2)	(3)
<i>Migrant</i>	0.218*** (0.038)	1.316*** (0.040)	-0.856*** (0.057)
<i>Migrant_Native</i>	0.106*** (0.039)	-0.251*** (0.037)	0.786*** (0.057)
Controls	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y
N	22896	22736	22864
Adj. $R^2$			
Pseudo $R^2$	0.108	0.188	0.105

» Return

## Inspecting Mechanisms II: Better Funding

	Number of Top VCs by Exits		
	<i>All</i> <sub>[t, t+3]</sub>	<i>Foreign</i> <sub>[t, t+3]</sub>	<i>Domestic</i> <sub>[t, t+3]</sub>
	(1)	(2)	(3)
<i>Migrant</i>	-0.100 (0.071)	1.262*** (0.115)	-0.296*** (0.075)
<i>Migrant_Native</i>	0.374*** (0.074)	-0.212* (0.111)	0.494*** (0.079)
Controls	Y	Y	Y
Industry × Est. Year FE	Y	Y	Y
N	21036	15812	20934
Adj. <i>R</i> <sup>2</sup>			
Pseudo <i>R</i> <sup>2</sup>	0.189	0.155	0.188

► Return

# Migrant Employees by Country of Origin

	Number of Workers Promoted After Departure $[t, t+5]$									
	India (1)	UK (2)	France (3)	Canada (4)	Philippines (5)	China (6)	Brazil (7)	Australia (8)	Mexico (9)	Spain (10)
<i>Migrant</i>	-0.353*** (0.128)	0.258*** (0.088)	0.247* (0.147)	0.034 (0.113)	-0.772*** (0.184)	-0.390*** (0.134)	0.409** (0.162)	0.169 (0.145)	-0.085 (0.192)	0.532*** (0.166)
<i>Migrant_Native</i>	0.627*** (0.125)	0.238** (0.093)	0.385*** (0.141)	0.360*** (0.115)	0.701*** (0.187)	0.570*** (0.145)	0.274* (0.154)	0.471*** (0.153)	0.449** (0.204)	-0.017 (0.165)
<i>Migrant_India</i>	2.996*** (0.132)									
<i>Migrant_Native_India</i>	-0.983*** (0.148)									
<i>Migrant_UK</i>		1.581*** (0.111)								
<i>Migrant_Native_UK</i>		-0.621*** (0.138)								
<i>Migrant_France</i>			2.647*** (0.152)							
<i>Migrant_Native_France</i>			-0.897*** (0.203)							
<i>Migrant_Canada</i>				1.847*** (0.151)						
<i>Migrant_Native_Canada</i>				-0.692*** (0.181)						
<i>Migrant_Philippines</i>					2.288*** (0.456)					
<i>Migrant_Native_Philippines</i>					-0.995** (0.492)					
<i>Migrant_China</i>						2.686*** (0.174)				
<i>Migrant_Native_China</i>						-0.852*** (0.224)				
<i>Migrant_Brazil</i>							3.051*** (0.197)			
<i>Migrant_Native_Brazil</i>							-0.557** (0.252)			
<i>Migrant_Australia</i>							2.203*** (0.217)			
<i>Migrant_Native_Australia</i>							-0.847*** (0.271)			
<i>Migrant_Mexico</i>								2.886*** (0.308)		
<i>Migrant_Native_Mexico</i>								-0.841** (0.344)		
<i>Migrant_Spain</i>									2.393*** (0.229)	
<i>Migrant_Native_Spain</i>									0.021 (0.314)	
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry $\times$ Est. Year FE										
N	16358	16021	13595	15099	12514	13893	12173	13018	11374	11516
Pseudo R <sup>2</sup>	0.288	0.125	0.152	0.115	0.083	0.114	0.140	0.113	0.124	0.161

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# Top VCs by Country of Origin

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

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