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MAPPING THE INSTITUTIONAL PIPELINE FOR GLOBAL AI TALENT

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ABSTRACT

Immigrants, particularly those from Asian Low- and Middle-Income Countries (LMICs), play a central role in U.S. frontier AI firms, yet the pathways that bring them into these positions are not well understood. We examine how U.S. universities serve as institutional intermediaries linking global talent to domestic firms. Using data on 1,757 AI graduates from top U.S. PhD programs alongside surveys and interviews, we develop a three-stage process model tracing how immigrant students move into, through, and beyond doctoral programs. We find that, compared to native students, immigrant students are more likely to match with diaspora faculty at entry, that advisor industry ties are more strongly associated with immigrants' participation in industry internships, and that internships are a common pathway through which immigrant graduates, particularly those from Asian LMICs, enter top AI firms. Our findings reframe skilled immigration into elite firms as a product of institutional intermediation, and reveal a pipeline whose functioning depends on specific relational structures that are vulnerable to disruption.

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A data appendix is available at http://www.nber.org/data-appendix/w33782

1 Introduction

Immigrants are widely recognized as important contributors to innovation. Immigrant scientists produce a disproportionate share of patents, high-impact publications, and breakthrough technologies in the United States (e.g., Stephan and Levin, 2001; Hunt, 2011; Bernstein et al., 2022), and the hiring of more immigrants increases firm performance (e.g., Beerli et al., 2021; Brinatti et al., 2023; Glennon et al., 2025). Frontier Artificial Intelligence (AI) firms in the U.S. in particular are strikingly dependent on PhD-trained global talent. Meta's Superintelligence Lab launched in 2025, for instance, hired 11 top AI scientists, each one of them an immigrant, mostly from India and China, and almost entirely with PhDs from U.S. universities (The Economic Times, 2025). The limited global supply of researchers capable of building these frontier systems is evident in the wages they command, with leading AI scientists at OpenAI, DeepMind, and Anthropic negotiating compensation comparable to that of elite athletes (Issac et al., 2025).

Given the importance of immigrant scientists to frontier AI, how firms source these employees is therefore a central, yet underexplored, question. Despite strong economic incentives on both sides, the labor market connecting global AI talent to U.S. firms has many frictions. Firms cannot easily evaluate foreign credentials or compare candidates trained in heterogeneous educational systems (e.g. Brücker et al., 2021; Chiswick and Miller, 2008; Lancee and Bol, 2017). Prospective employees from abroad face legal barriers to entry, as employment-based visas are tightly rationed and allocated by lottery in the U.S. (Glennon, 2024). And the professional networks through which job market information flows are geographically segmented (Schmutte, 2015; Dustmann et al., 2016), leaving global talent pools disconnected from hiring firms in the U.S. (Saxenian, 2007).

Institutional intermediaries, specifically doctoral programs in U.S. universities, can play a central role in resolving these frictions and shaping how global AI talent reaches U.S. frontier firms. Prior work has shown that U.S. universities can facilitate the channeling of foreign talent into the U.S. workforce, attributing this largely to the comparatively accessible legal entry that student visas provide when direct employment routes are constrained (Bound et al., 2015; Amornsiripanitch et al., 2021). But beyond facilitating a legal channel, we know little about how the intermediating role of U.S. universities actually works.

In this paper, we examine how doctoral programs in U.S. universities support the transition of immigrant talent into elite U.S. AI firms. In doing so, we show that what matters is not just the university as a legal pathway, but the relational structures operating within it, including diaspora faculty who can evaluate and recruit from foreign universities, advisor networks that connect students to industry opportunities, and internships that give firms a way to screen students whose credentials they cannot easily interpret. These structures support immigrant students, but they also solve a problem for firms, who face uncertainty when recruiting from unfamiliar talent pools.

To develop an account of this role of U.S. universities we undertake a process study (Van de Ven, 2007; Langley et al., 2017) that traces the sequential process through which immigrant AI talent enters, navigates, and moves beyond U.S. doctoral programs, drawing on literature on coethnic clustering, doctoral influence, and scientific labor markets. A process approach is essential because the intermediation cannot be observed at a single point in time: the challenges faced by immigrants and hiring firms arise at different stages, and these stages are shaped by distinct relational structures. We investigate how these structures operate and how they influence the movement of global AI talent into U.S. frontier firms, where academic and industry research is deeply integrated and the demand for PhD-trained immigrants is particularly high.

Our analysis draws on unusually rich data that allow us to observe this process: (1) longitudinal career histories of 1,757 AI PhD graduates from top U.S. programs (assembled by the Center for Security and Emerging Technology at Georgetown University), (2) detailed profiles of their doctoral advisors, (3) complete publication and industry collaboration data, (4) original surveys fielded to both students and advisors, and (5) qualitative interviews that illuminate the relational structures underlying key transitions. These combined sources allow us to reconstruct the flow through which immigrant talent moves from their origin countries to U.S. doctoral programs to frontier AI firms. By comparing native students to immigrants trained in the same programs, we are able to identify immigrant-specific patterns.

Our sample of AI PhD graduates from top U.S. programs is highly international: over half are immigrants, as defined by the location of their undergraduate degree, and almost 30 percent are from Asian Low- and Middle-Income countries (LMICs), predominantly India and China. These patterns in part reflect the broader initial conditions shaping the global-to-U.S. AI talent pipeline. Strong global push–pull forces and U.S. immigration policy make doctoral training an important entry point into the U.S. innovation system, particularly for highly skilled individuals from abroad. Within this context, immigrant students in our sample appear distinct from the outset, reporting stronger industry-oriented goals prior to entering the PhD. These initial conditions set the stage, but leave open the question of how immigrant students actually navigate doctoral training and reach elite firms. Our three-stage process model traces how specific relational structures at different points in doctoral training resolve the challenges that separate global talent from U.S. firms.

Stage 1 (Entry and Matching) focuses on how students match with advisors across national borders. Applicants from foreign educational systems are difficult for domestic admissions committees to evaluate, and students themselves face uncertainty about which programs and advisors will be the right fit. In the data, immigrant students, particularly those from Asian LMIC countries, are more likely to be advised by faculty from their home countries than would be expected under random advisor assignment. Survey and interview evidence points to why: diaspora faculty possess deeper familiarity with foreign institutions and grading norms, are more likely to have prior contact with prospective students through home-country academic networks, and serve as visible points of entry for applicants navigating an unfamiliar system. These patterns are consistent with the broader dynamics of coethnic clustering, where shared national or ethnic ties transmit trust, information, and opportunities when formal signals are incomplete (Freeman and Huang, 2015; Kalnins and Chung, 2006; Kerr and Mandorff, 2023; Marinoni, 2023; Nanda and Khanna, 2010; Åslund et al., 2014; Kerr and Kerr, 2021).

Stage 2 (Training and Industry Engagement) examines participation in industry-facing activities during the PhD. In AI, the boundary between academia and industry is relatively porous, and doctoral students frequently engage with firms through collaborations, internships, and applied research. While immigrant students enter doctoral training with stronger industry-oriented career goals, access to these opportunities is not entirely self-organized. Prior research suggests that advisors and the doctoral environment play an important role in structuring students' exposure to industry-facing activities (Azoulay et al., 2017; Roche, 2023; Gaule and Piacentini, 2018). These relational channels may be particularly important for immigrant students, who often have more limited access to domestic professional networks and tacit labor-market knowledge than native students (Granovetter, 1995; Lancee, 2013). Consistent with this, our data reveal systematic differences in industry engagement: students from Asian LMIC countries tend to participate more intensively in industry-linked research environments, such as advisor-facilitated internships. But not only are they engaging with industry at higher rates, we find that the relationship between advisor industry ties and students' industry engagement is significantly stronger for students from Asian LMIC countries, and that this effect is especially pronounced in contexts where formal university–industry pipelines are less developed. Together, these findings suggest that advisor-mediated channels may help connect immigrant students to industry opportunities when other professional networks are less accessible (Lin et al., 2001; Kalnins and Chung, 2006; Wilson and Portes, 1980).

Stage 3 (Industry Transition) examines how doctoral experiences relate to students' entry into the labor market. A large literature on scientific labor markets highlights that sorting into industry versus academia reflects the interaction of preferences, abilities, perceived fit, and exposure to opportunities (e.g., Stern, 2004; Agarwal and Ohyama, 2013; Roach and Sauermann, 2010, 2024; Sauermann and Roach, 2012). For immigrant talent, however, these dynamics are compounded by firm-side uncertainty: employers hiring from global talent pools may face uncertainty when evaluating candidates from unfamiliar environments (Bidwell, 2011; Lancee and Bol, 2017). In the data, immigrants, and especially graduates from Asian LMIC countries, are more likely than natives to take industry jobs, particularly at top AI firms, even after extensive controls and without clear evidence of lower academic ambition. Internships appear to play an important role in this pattern: among Asian LMIC graduates employed at top AI firms, internship-based entry is substantially more common than for other groups. These patterns are consistent with the possibility that internships serve both as an important pathway for immigrant students and as a screening mechanism for firms.

Together, these stages reveal that the concentration of immigrant AI researchers, especially those from Asian LMIC countries, in elite U.S. firms is not simply the product of economic incentives, self-selection, or individual preferences. It is an outcome of institutional intermediation in which specific relational structures within universities (diaspora faculty, advisor-industry networks, and internship pipelines) resolve frictions on both sides of the market that would otherwise prevent global talent from reaching top firms.

The paper's primary contribution is to show that the movement of skilled immigrant scientists into U.S. frontier firms is structured by institutional intermediation that resolves numerous challenges that immigrants face. Prior research on skilled migration has tended to treat immigrant talent as exogenous to firms, emphasizing economic incentives and migration costs (e.g. Borjas, 1987; Grogger and Hanson, 2011), or documenting disproportionate contributions to innovation and firm performance (e.g., Stephan and Levin, 2001; Beerli et al., 2021; Brinatti et al., 2023; Glennon et al., 2025; Hunt, 2011; Bernstein et al., 2022) without examining the upstream institutional relational processes through which immigrants come to be hired. We fill this gap by identifying the specific mechanisms through which universities channel global talent into a small set of top firms.

In developing this account, we also contribute to research on hiring and talent pipelines (e.g., Brymer et al., 2014, 2019) by showing how universities function as upstream labor-market infrastructure that is especially consequential for immigrant scientists, and to the scientific labor markets literature (Stern, 2004; Agarwal and Ohyama, 2013; Roach and Sauermann, 2010; Sauermann and Roach, 2012; Roach and Sauermann, 2024) by demonstrating that sorting into industry versus academia reflects cumulative institutional and relational mechanisms, not stable preferences or contemporaneous labor-market conditions alone.

Finally, these findings highlight a structural vulnerability in how frontier AI firms access talent. Because the university's intermediating function depends on specific relational structures rather than on the institution as a monolithic entity, the pipeline is fragile to targeted disruptions. Constraints on international student enrollment reduce legal access. Limitations on the hiring of immigrant faculty diminish the diaspora networks that mediate entry. Reductions in industry-university collaboration limit the internship and screening channels through which firms resolve uncertainty about foreign-trained candidates. Each of these disruptions can break a distinct stage of the pipeline. Firms that depend on this talent may find that their access is contingent on institutional arrangements upstream of their own hiring processes.

2 The Economic and Policy Forces Shaping Global AI Talent Flows

This section provides background on the macroeconomic and policy landscape that form the initial conditions under which the global-to-U.S. AI talent pipeline operates. These forces shape who seeks entry into the U.S. innovation system and why doctoral training emerges as a primary legal and organizational pathway. They do not, however, examine how global talent actually navigates that pathway, a question that motivates the process model developed in the sections that follow.

2.1 Economic Foundations of the U.S. AI Labor Market

Artificial intelligence differs from many other technological domains in the resources required to compete at the frontier. Specifically, cutting-edge AI depends on three critical inputs: vast computing power, access to large-scale datasets, and a highly skilled workforce of researchers (Ahmed et al., 2023). The sector is unusual in that the same systems that drive commercial applications also constitute the scientific frontier: the largest models simultaneously advance basic research and power deployed technologies. As a result, frontier AI research is increasingly concentrated in industry or in industry-university collaborations, where access to compute and data is feasible (Ahmed et al., 2023).

The United States has long dominated the global AI landscape (Stanford University Human-Centered Artificial Intelligence, 2025). Training state-of-the-art AI models has increasingly required data centers stocked with tens of thousands of specialized chips. These facilities are scarce: only 32 countries worldwide host AI-specialized data centers, and the vast majority are concentrated in the United States, China, and the European Union (Satariano, 2025). The United States dominates even within this elite club; American firms operate nearly two-thirds of the world's AI computing hubs, and Nvidia designs the chips that power most large models. Meanwhile, American firms generate the proprietary, globally scaled datasets that make it possible to train models at scale.

PhD-trained talent is the final critical input, and here too the United States exerts disproportionate pull. Frontier AI development depends on a small pool of researchers with deep technical training in machine learning, optimization, and large-scale systems, many of whom are foreign-born but trained in U.S. doctoral programs that sit at the center of global research and industry networks. The importance of this training pipeline is reflected in firms' hiring practices. For example, when Meta launched its Superintelligence Lab in 2025, its recruitment of senior AI scientists drew from a short list of globally recognized researchers, the vast majority of whom held PhDs from U.S. universities, despite originating from outside of the United States. A consequence of this integration between academic and industrial research is that, unlike in most scientific fields, industry positions at leading AI firms offer access to frontier research opportunities, including large-scale compute, proprietary datasets, and collaborative teams, that often rival or exceed what is available in academic departments. As one advisor in our sample explained, students are drawn to firms that *"have big compute clusters, and they can spend way more...it's often more attractive for them."* For doctoral advisors, this means that placing students in top industry labs does not represent a loss of scholarly legacy; rather, it reflects a placement into an alternative, and in many cases, superior, research environment. This distinguishes AI from fields where industry careers are viewed as departures from the scientific frontier.

These conditions create strong incentives for researchers worldwide to seek entry into the U.S. AI ecosystem, which then intersect with broader push–pull forces that shape the global market for AI talent.

2.2 Push-Pull Forces in the Global Market for AI Talent

The concentration of AI talent in the U.S. is enabled by the convergence of three forces: (1) high wages and research opportunities in the U.S., (2) rapid expansion of undergraduate education in sending countries, and (3) limited opportunities for advanced training and high-level research at home.

A long tradition in the economics of migration emphasizes that international mobility responds strongly to expected earnings differentials and policy-determined access to destination labor markets. Classic models highlight how wage gaps and migration costs shape migrant self-selection (Borjas, 1987), and subsequent work shows that educated immigrants are particularly responsive to host-country economic and institutional conditions. Empirical evidence demonstrates that foreign-born scientists and engineers disproportionately enter U.S. STEM fields when domestic opportunities expand (Bound et al., 2015; Hunt, 2011; Khanna and Morales, 2025), and that immigrants are more likely to move to high-opportunity locations (Abramitzky and Boustan, 2022).

These economic pull forces intersect with the rapid expansion of higher education in Asia and other emerging regions. China's 1999 higher education reform alone increased annual college admissions nearly tenfold, from about 1 million in 1998 to over 9 million by 2020, while the number of universities more than doubled (Jia et al., 2025). Similar trends unfolded in India, where postsecondary enrollment rose from 6 million in 1997 to more than 33 million by 2017 (Bound et al., 2021; National Science Foundation, 2023). In both cases, the expansion of undergraduate and master's education outpaced the development of domestic research infrastructure and high-skill employment opportunities, particularly in AI-intensive fields. The result has been a structural surplus of technically trained graduates relative to local opportunities, increasing the appeal of the United States.

As the next subsection details, universities play a central role in translating these incentives into realized migration, serving as an institutional bridge that connects global talent supply to U.S. labor demand, in part because of the U.S. immigration system.

2.3 Universities, Visas, and the Legal Ladder into the U.S. AI Industry

While the economic motivations to come to the U.S. are strong, access to the U.S. labor market for foreign nationals is not automatic. The United States operates a demand-driven skilled-immigration regime in which employer-sponsored visas are tightly rationed and highly uncertain at the point of labor market entry.[1] By contrast, the student route is comparatively accessible and temporally flexible.

Several features position U.S. PhD programs as a reliable "legal ladder" into the U.S. AI sector. PhD programs provide cap-free lawful entry through F-1 visas [2], time-limited post-graduation work authorization after graduation through OPT and the STEM-OPT extension,[3] and repeated opportunities to convert to employer sponsorship (H-1B or other categories), all while embedding students inside the country's leading research–industry networks. Indeed, recent evidence (e.g., Bound et al., 2015; Amornsiripanitch et al., 2021) demonstrates that the central role of universities in channeling foreign STEM talent into U.S. employment

[1]The dominant employer sponsor visa is the H-1B, which is capped at 85,000 annually (including a 20,000 carve-out for U.S. advanced degrees) and allocated by lottery whenever demand exceeds supply, a situation that has prevailed every year since 2004, with selection rates around 42 percent in FY2022 (Glennon, 2024). Universities and other research nonprofits are exempt from these H-1B caps.

[2]The F-1 student visa is not subject to annual numerical caps, making it far more accessible than employer-sponsored categories. Recent evidence shows that the F-1 is in fact the dominant legal channel through which high-ability international students enter the United States (Shih, 2016).

[3]"Optional Practical Training". The standard OPT authorization is 12 months, but STEM graduates receive up to 36 months, a reform that measurably increased the likelihood of international students' enrollment in OPT-eligible STEM fields (Khosla, 2018; Amuedo-Dorantes et al., 2019) and transitions into the U.S. workforce for STEM graduates (Guo et al., 2024). Crucially, OPT is also cap free.

arises at least in part from the structure of U.S. visa policy, which restricts direct work entry while keeping student routes comparatively open.

These visa structures do not merely shape entry into the U.S.; they also condition how students perceive the feasibility of different career paths after graduation. International graduates face temporal pressures from OPT deadlines and uncertainty in H-1B allocation, which can make extended academic pathways which often require postdoctoral positions appear riskier than industry roles with established visa sponsorship infrastructure. Students and advisors in our sample consistently emphasized these constraints. As one student explained: *"as an international student, it's much riskier to go the postdoc route, because if you use up your OPT, you're then screwed."* An advisor similarly noted: *'several of my former students who are international...found employment with large firms who could facilitate visa issues.'* On the demand side, visa caps and sponsorship costs may make some employers, particularly smaller firms and universities with limited administrative capacity, less willing to hire international candidates.

In addition to serving as a legal gateway, U.S. universities dominate global rankings in computer science and engineering (Symonds, 2025) and also function as central nodes linking research and industry. AI departments at leading universities routinely collaborate with firms through sponsored research projects, joint labs, and dual academic–industry appointments.[4] Doctoral students are frequently embedded in these arrangements, gaining exposure to cutting-edge research and often securing internships that serve as direct pipelines into employment. These arrangements blur the boundary between academic training and industrial participation, making universities both entry points and institutional bridges within the U.S. AI labor market.

Taken together, these economic and policy dynamics constitute the initial conditions shaping how global AI talent enters the U.S. doctoral system. They structure why highly skilled international candidates, especially from certain countries, might view U.S. PhD programs as a viable pathway into the American innovation economy. But while the visa structure provides legal access, significant challenges remain. For example, immigrants face information asymmetries in applying to and choosing U.S. university doctoral programs even as admissions committees struggle to evaluate foreign credentials from heterogeneous educational systems. The professional networks through which opportunities flow are geographically segmented, leaving immigrant students with weaker connections to domestic labor markets. And employers may face uncertainty when screening candidates from unfamiliar initial environments. In what follows, we use rich administrative data, together with novel survey results and interviews, to document how relational structures within universities resolve these challenges, shaping the processes through which immigrant researchers move from doctoral entry to firm employment.

[4]See, for example the MIT-IBM Watson AI Lab (`https://mitibmwatsonailab.mit.edu/`) or the Columbia Center of AI Technology (`https://cait.engineering.columbia.edu/`) which is a partnership between Columbia Engineering and Amazon.

3 Data Sources and Measures

3.1 Sample of Artificial Intelligence PhD Students

Our primary sample is PhD students who (1) graduated between 2014 and 2018 from one of the twenty highest-ranked U.S. PhD-granting institutions in artificial intelligence (AI)-related fields, (2) have publicly available employment and educational histories, (3) wrote an AI-related dissertation and (4) for whom at least one PhD advisor is known. The original sample was collected by the Center for Security and Emerging Technology (CSET), who also determined whether a dissertation was AI-related or not using a keyword approach on all dissertations that could be found in ProQuest.[5] Importantly, these individuals were selected based on whether their dissertation was related to AI, not by whether they were in a computer science department.

CSET also collected comprehensive education (undergraduate and graduate degrees, including institution, department, advisor name(s) and graduation date) and career histories (employer, job title, and employment dates) for each student. Coverage spans the period prior to the PhD, the duration of the PhD (including internships), and up to six years after completion.[6] Employers are manually categorized into two main groups: academia and industry.[7] To address missing entries, we supplemented the dataset with targeted manual searches. For our primary analysis, we focus on the first job post-PhD, because this is the choice most likely to be shaped by the structured pathway mediated by universities.

We added several new fields to the CSET data. First, we classify PhD institutions in our sample into top ten and bottom ten in AI, based on the 2018 U.S. News University Rankings.[8] Second, we proxied for "top industry employers" by identifying both the so-called "FAANG" companies (Facebook, Amazon, Apple, Netflix and Google, which collectively account for almost ten percent of the U.S. stock market's total capitalization),[9] and the best-rated AI employers in 2018, as reported by Forbes (via Glassdoor) and Business Insider.[10] The latter includes Nvidia, Adobe, Microsoft, Tesla, Intel, Spotify, IBM, Snap, Disney, Airbnb, Uber, Accenture, Wells Fargo, Samsung, MoTek Technologies, Lenovo, and Rakuten Marketing. We combine these firms into a single indicator variable equal to one if a sample student worked at any of them post-PhD.

Third, we add an immigrant indicator field. As we do not have access to the country of birth or visa status of the sample students, we use a proxy for immigration status: whether or not they completed their

[5] A comprehensive full-text query of all PhD dissertations was used to identify AI related theses, using phrases such as "information retrieval", "autonomous vehicles" and "random forest". False positives were then filtered out, i.e., dissertations using keywords in a context unrelated to AI and machine learning.

[6] Data collection took place in 2020, so data on more recent graduates is truncated.

[7] Note that a third category is comprised of government and non-profit organizations. However, we focus on industry or academic job outcomes given that 98% of our sample occupy either academic or industry jobs across any job.

[8] We use this broad institution rank to mirror CSET's sample collection strategy, but also collect alternatives measures of program rank at the university-department level from NRC (https://www.nature.com/nature-index/research-leaders/2025/institution/all/all/global) and QS (https://www.topuniversities.com/subject-rankings) ranking websites.

[9] https://corporatefinanceinstitute.com/resources/equities/faang-stocks/

[10] https://www.forbes.com/sites/louiscolumbus/2017/11/26/the-best-ai-companies-to-work-for-in-2018-based-on-glassdoor; https://www.businessinsider.com/top-companies-ivy-league-computer-science-graduates-most-want-to-work-2018-6#28-samsung-3

undergraduate degree outside of the United States. This measure provides us with a conservative estimate; it will not include those who immigrated to the U.S. at a young age or for college, but reassuringly, students who immigrated before college constituted a relatively small share of U.S. undergraduate enrollment during our observation period: approximately 3% in 2011 (Bound et al., 2015) and 5.6% in 2022 (Batalova, 2024). Native students serve as the comparison group throughout our analysis, allowing us to identify the mechanisms that differentially shape immigrant trajectories within the same institutional environments.

For much of our analysis, we distinguish between two groups of immigrant students. The first group, which we label "Asian LMIC immigrants", consists of students who completed their undergraduate education in low-, lower-middle, or upper-middle-income Asian countries, specifically Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka or Vietnam (522 students – of which 96% are from India and China).[11] The second group, which we label "Other immigrants" comprises all other immigrant students, defined as students with undergraduate education outside the United States but not in one of the listed Asian LMICs (396 students).

We separate Asian LMIC immigrants from the rest of the immigrants for two key reasons, both related to the economic forces described in Section 2. First, individuals from LMICs face the sharpest wage and opportunity differentials vis-à-vis the United States, and thus are particularly responsive to the economic incentives that the U.S. AI industry provides. Second, the Asian talent base, and in particular India and China, is uniquely consequential in scale, yet both countries' doctoral and industrial research capacities remain constrained relative to their graduate output.

Our main sample consists of 1,757 AI PhD students. As shown in Table 1, just over half of the PhD students in our sample are immigrants, with 30% of the sample from Asian LMIC countries. Appendix Table A1 provides a detailed breakdown of undergraduate countries: Chinese immigrants make up the largest portion (20% of the full sample), followed by Indian immigrants (8%). Immigrants from high-income countries (using the World Bank definition of high-income countries) comprise 11% of the full sample. Table 1 also reports the U.S. institutions and departments from which sample students earned their PhDs.[12] Over 40% of the sample graduated from engineering departments and about 30% graduated from mathematics and computer science departments. The table further lists the ten most common post-graduate employers. Four of these, all large private sector firms (Google, Facebook, Microsoft, and Amazon), stand out for especially high rates of Asian LMIC immigrant hires (38-55%), compared to both the sample average of 29% and to other immigrant hires (12-26%). By contrast, academic employers such as MIT, Stanford, Harvard, and Princeton do not exhibit such overrepresentation, with the balance tilted more towards natives.

To complement the career data, we match the PhD students in our sample to their full publication history using the OpenAlex API. A key challenge in using publication databases is the common name prob-

[11] Asian origin countries are defined using the NCES classification: https://nces.ed.gov/ipeds/report-your-data/race-ethnicity-definitions. Country income classifications are based on the World Bank country groupings for 2014 to 2018 inclusive: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.

[12] We standardize department names into broad categories.

lem. Fortunately, OpenAlex generates scientist identifiers and assigns publications (including conference proceedings and preprints) based on topic, collaboration patterns, and institutional affiliation. We extract publications for each sample student and refine matches by restricting them to known affiliated institutions within a five-year window.[13]

From these matched records, we construct annual publication counts, distinguishing between output prior to, during, and after the PhD. We also measure collaboration patterns by identifying industry-affiliated coauthors, as defined by OpenAlex's institutional classification. Finally, we assess the topical orientation of pre-graduation publications. For each student, we extract OpenAlex-tagged concepts[14] and calculate an "industry orientation" score. This score is defined as the ratio, in the year of graduation, of U.S.-based publications using a concept authored by industry researchers to those authored by academic researchers. Averaging across all concepts used in pre-graduation publications yields a measure of the extent to which their research topics align more closely with industry- versus academia-oriented work.

Table 2 shows the raw differences in each of the main variables described above between natives, Asian LMIC immigrants, and other immigrant PhD students.[15]

Graduation year does not differ significantly between groups, but nearly all other characteristics do. For instance, immigrant students appear much more productive prior to their PhD graduation, with an average of 8.3 pre-PhD-graduation publications for Asian LMIC immigrants and 5.8 for other immigrants, compared to 4.4 for natives. At the same time, immigrants are less likely than natives to have trained at a top ten-ranked PhD program (47-58% versus 64%). Immigrant PhD students are also more likely to have an immigrant advisor (53% versus 33% for natives), and their advisors have more publications with industry collaborations in the five years preceding the PhD. In the raw data, immigrant PhD experiences appear to also differ from those of native students: immigrants, particularly Asian LMIC immigrants, are much more likely to undertake an industry internship during their PhD.

Post-graduation employment patterns are strikingly similar in one respect and sharply different in another. More than 90% of PhD students across all groups remain in the U.S. following graduation, consistent with prior evidence on high stay rates of immigrant doctoral students (Finn, 2010). But first job placements diverge: immigrants, especially Asian LMIC immigrants, are more likely to enter industry roles (70% for Asian LMIC students, 58% for other immigrants, versus 51% for natives), whereas natives are more likely to enter academia (43% versus 29-38% among immigrants). Immigrants, again especially Asian LMIC immigrants, are also more likely to take their first job at a top AI industry employer (51% for Asian LMIC immigrants, 38% for other immigrants, versus 26% for natives). These baseline differences underscore systematic variation in early career trajectories, to which we return in the next section.

[13] To resolve remaining ambiguities, such as multiple OpenAlex identifiers with the same name and affiliation, we exclude identifiers who never publish in computer science and use advisor and department information to identify the best match(es).

[14] Each work in OpenAlex is tagged with multiple concepts using an automated classifier that draws on the title, abstract, and venue information.

[15] Appendix Table A3 aggregates immigrants into a single group for comparison with natives.

3.2 Advisor Details

We also construct advisor-level data for the 1,408 unique advisors of our sample students.

First, mirroring our classification of PhD students, we identify whether each advisor completed their undergraduate degree in the United States or abroad in order to classify as native advisor, Asian LMIC advisor, or other immigrant advisor.[16] Appendix Table A2 reports the distribution of undergraduate countries for all advisors. Among immigrant advisors, India and China are the most common undergraduate locations, followed by Canada, the United Kingdom, and Israel. We also classify advisors by name nationality using the NamePrism algorithm applied to both first and last names for supplementary analysis.

For each PhD student, we then record whether at least one of their advisors shares their undergraduate degree country and, as a supplementary measure, whether at least one advisor shares their name nationality.[17]. Our preferred measure of conationality is shared undergraduate country.

Finally, we merge publication data to each advisor using the same procedure applied to students: searching OpenAlex by advisor name and institution, and refining matches manually. For each advisor, we count authored publications in the five-year window prior to the focal student's PhD start year, thereby excluding publications that may have been influenced by the student. In addition, we record the number of industry-affiliated coauthors, and industry funded publications, as identified by OpenAlex.

3.3 Survey and Interview Data

To explore the mechanisms driving our main results we conducted surveys of all sample students and their PhD advisors, respectively. Out of our sample of 1,757 PhD students and 1,408 unique advisors, we found email addresses for 1,577 and 1,304 people respectively. After a first round of emails followed by a reminder email two weeks later, 14% and 10% respectively completed the survey.[18]

The PhD student survey asked questions about program and advisor selection, original career plans, and factors influencing their first job choice. We also asked them about their country of origin to cross-check our own immigrant definition.[19] The advisor survey asked questions about PhD student selection and why their students might have ended up going into industry or academia, as well as questions about how many students they had advised and where they are originally from. Both students and advisors were asked whether they would be willing to interview with us. We conducted interviews with five individuals between February 26 and March 21, 2025 on Zoom. All survey tools can be found in Appendix D.

[16] Information on advisors' undergraduate institutions was collected from department websites and online resumes.

[17] Over 85% of our sample have just one advisor. 12% have two, and ten students have three or more. This breakdown is almost identical across immigrants and natives.

[18] See Appendix Table D1 for response rate variation across sample subgroups.

[19] Reassuringly, our immigrant definition in the respondent sample is fairly accurate; we had correctly labeled 81 percent of the true immigrants as immigrants and 98 percent of the true natives as natives using our undergraduate country of origin definition.

4 A Three-Stage Process Model of the Global-to-U.S. AI Talent Pipeline

In this section, we develop a process model of the global-to-U.S. AI talent pipeline, shown schematically in Figure 1. The model conceptualizes universities as institutional intermediaries that resolve a series of frictions separating global talent from U.S. firms. It traces how specific relational structures within universities (diaspora faculty, advisor-industry networks, and internship pipelines) address challenges that arise sequentially as students move into, through, and beyond U.S. PhD programs.

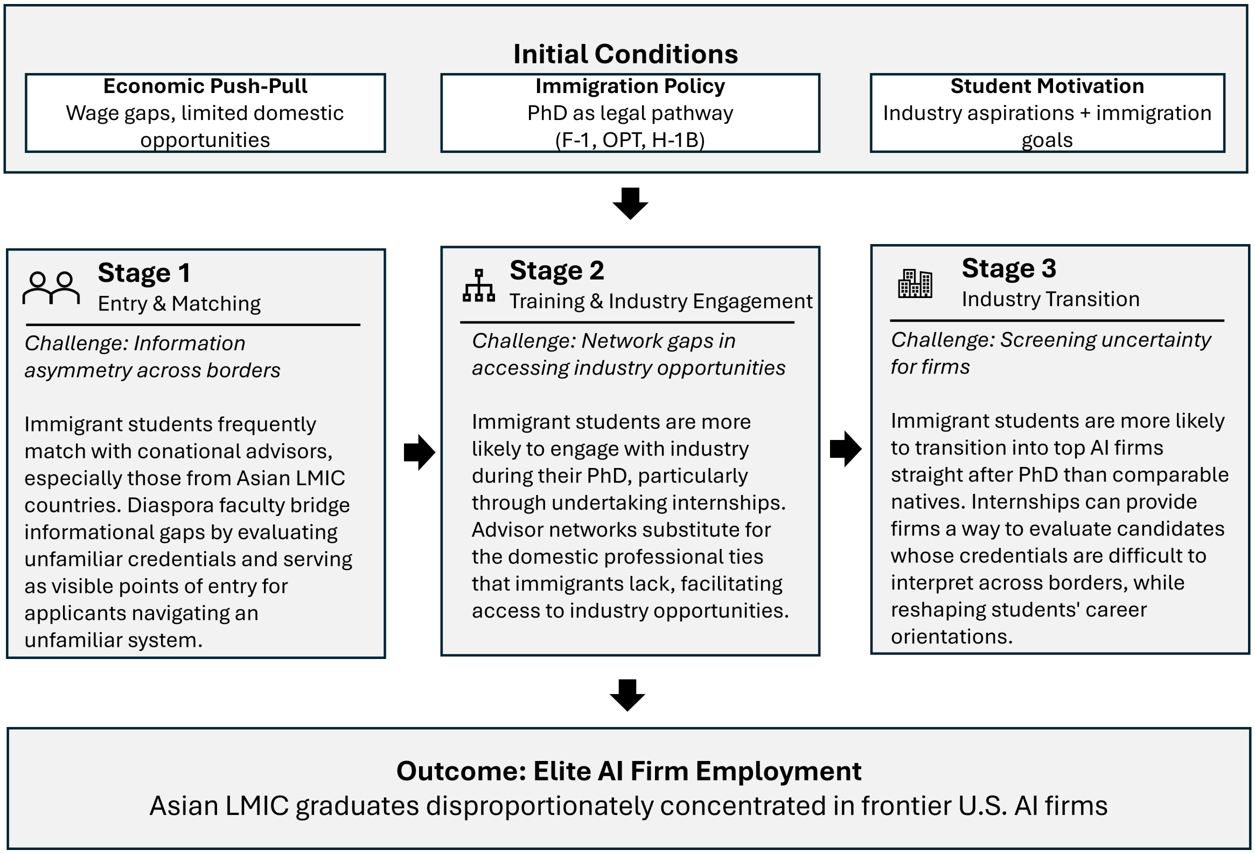
As illustrated at the top of Figure 1, and outlined in section 2, this process is shaped by a common set of initial conditions. These include strong economic push-pull forces between sending countries and the United States, the structure of U.S. immigration policy that positions the PhD as a viable legal pathway into the labor market, and student motivations that often combine industry aspirations with longer-run immigration goals. But legal access alone does not overcome the challenges that separate global talent from U.S. firms.

The model, illustrated in Figure 1, traces three sequential stages, and distinct relational structures that resolve these key challenges that immigrants face. Stage 1 (Entry and Matching) examines how students match with advisors across national borders; diaspora faculty may facilitate entry as immigrant students face information asymmetries in applying to, and joining U.S. university programs. Stage 2 (Training and Industry Engagement) examines students' exposure to industry opportunities during the PhD; advisor networks may help facilitate access because immigrant students often have more limited professional connections and knowledge of labor-market norms. Stage 3 (Industry Transition) examines how doctoral experiences relate to entry into the labor market; internships may help provide experience and allow firms to evaluate candidates whose credentials are otherwise difficult to interpret, which may be particularly important for students from unfamiliar educational systems.

The trajectory of Ji Lin provides a concrete illustration of this process for an Asian LMIC immigrant student. Ji Lin completed his undergraduate studies in China, pursued a PhD at MIT under Professor Song Han (himself Chinese-born), collaborated extensively with industry during his doctorate, and later joined Nvidia and OpenAI to contribute to frontier systems such as GPT-4. This trajectory is representative of a broader pattern that recurs throughout our data for immigrants, and especially for Asian LMIC students: entry into U.S. doctoral programs mediated by diaspora advisors, intensive engagement with industry-facing research during the PhD, and transition into frontier AI firms immediately after graduation.

The following subsections elaborate on each of the stages described in Figure 1, documenting how the relational structures within universities resolve the challenges that would otherwise prevent global AI talent from reaching frontier firms, and in doing so contribute to producing the observed concentration of immigrant AI talent, particularly from Asian LMIC countries, in frontier U.S. firms.

Figure 1: Global-to-US AI Talent Pipeline



Notes: This figure illustrates the three-stage process model of the global-to-U.S. AI talent pipeline. Initial conditions (economic push-pull forces, immigration policy, and student motivations) shape entry into the system. Stage 1 (Entry and Matching) shows how students access doctoral programs through diaspora advisors. Stage 2 (Training and Industry Engagement) depicts engagement with industry-linked research environments during the PhD. Stage 3 (Industry Transition) shows the pathway from doctoral training to employment in elite AI firms.

4.1 Who enters the pipeline?

Before turning to the mechanisms that operate within the doctoral pipeline, it is important to clarify who enters it. As indicated in the top panel of Figure 1, global AI PhD entrants arrive with heterogeneous motivations and constraints shaped by economic push-pull forces and the structure of U.S. immigration policy. While these macro forces were discussed in detail earlier in the paper (Section 2), here we focus on how they are expressed at the point of doctoral entry.

For many immigrant students, the decision to pursue a doctorate in the United States is shaped not only by research considerations but also by the legal and temporal access to the U.S. labor market that doctoral study affords. Interviews and survey responses consistently affirm this logic. In open-ended responses, several students emphasized that doctoral study offered a rare legal pathway into the United States, citing obtaining a student visa or a "desire to immigrate" as key motivations. Others described the PhD as a way to secure temporary work authorization and explore long-term residence options, even noting that *"you're missing the U.S. visa option"* among the survey choices.

The importance of this pathway into the U.S. labor market is also reflected in differences in student motivations. In our survey, 37% of foreign respondents cited industry career opportunities as an important or very important reason for pursuing a PhD in the U.S., rising to 42% among Asian LMIC students. Moreover, as shown in Appendix Figure A1, Asian LMIC students reported greater industry- versus academic-related goals prior to starting the PhD program, compared to other immigrants and native students. In summary, students arrive with more pronounced industry aspirations, potentially reflecting the viability of this migration pathway into the labor market in the U.S., as well as the relative attractiveness of industry career pathways to immigrants.[20]

These initial differences provide the starting point for the process model developed in this section. In the next subsection, we examine the first stage of this process by analyzing how these students enter the doctoral pipeline through advisor matching.

4.2 Stage 1: Entry and Matching

Doctoral advising is a critical organizational relationship in graduate education, linking the process of recruitment, training, and placement. These functions take on heightened importance in internationalized doctoral systems such as that of the United States, where temporary visa holders earned 39 percent of all S&E PhDs awarded in 2023 (National Science Foundation, 2023). For applicants from foreign educational systems, prior credentials, letters, and institutional reputations are often difficult for admissions committees to interpret. Students themselves face uncertainty about which programs and advisors will be the right fit. Faculty judgments therefore play a pivotal role in assessing quality and fit, translating heterogeneous educational signals into evaluations that committees can compare. Once students arrive, advisors continue to shape how they navigate linguistic, cultural, and institutional barriers.

The central role of advisors raises the question of which advisors are involved in immigrant entry and mentoring, and how these relationships form in the first place. In academia, students and advisors often rely on shared identities when forming advising relationships: for example, women are more likely to match with female advisors, and these matches are associated with higher productivity and career advancement (Gaule and Piacentini, 2018). Coethnic or conational ties have been observed to play analogous roles in other settings, shaping matching, learning, and occupational concentration in labor markets, entrepreneurship, and collaboration networks (Kalnins and Chung, 2006; Kerr and Mandorff, 2023; Freeman and Huang, 2015). We examine whether similar dynamics operate in doctoral advising, and with what consequences for immigrant entry into the pipeline.

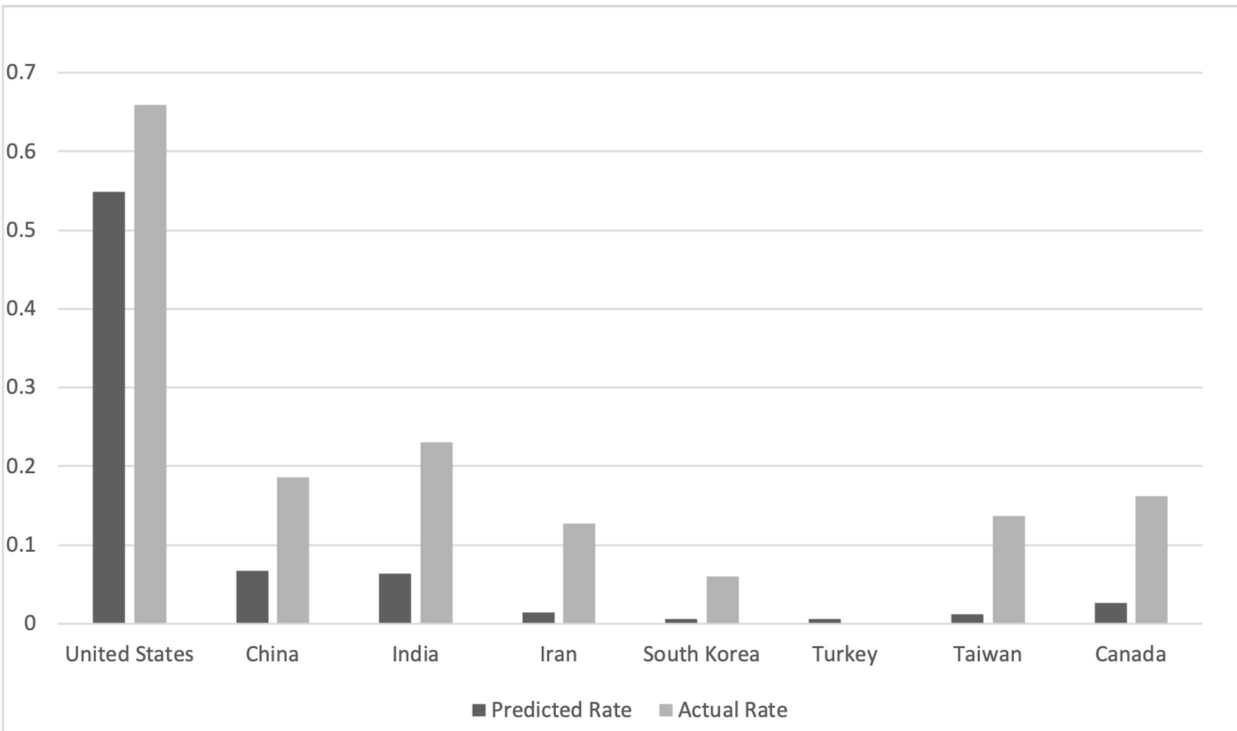
The immigrant students in our sample, as the descriptive evidence already suggested, are more likely to be advised by immigrant faculty, or those who share their own background. Appendix Figure C1a illustrates the directional flow of students to U.S. advisors by undergraduate country group. Conational

[20] This could also include the temporal pressure of the U.S. visa regime. International graduates must secure qualifying employment within the STEM OPT window and may face uncertainty in the H-1B lottery. These timelines can make industry roles, especially those with established sponsorship infrastructures, appear more viable than extended academic pathways.

advisor-advisee matching, regardless of nationality, is apparent in the figure. But there are particularly strong links between Asian LMIC undergraduates and Asian LMIC advisors.

These patterns are not driven by mere advisor availability. Figure 2 compares predicted and actual conational match rates, where the predicted rate assumes random assignment of students to advisors based on the composition of the advisor pool.[21] For example, if 50% of advisors earned their undergraduate degree in China, then the predicted probability of any student (Chinese or not) matching with a China-educated advisor is 0.5. Across all groups, actual match rates exceed predicted rates, and the gap is especially pronounced for students from China and India.[22]

Figure 2: Predicted and Actual Rate of Conational Matching



Notes: Predicted matching rates assume random assignment of students to advisors, reflecting the proportion of advisors in our sample who obtained their undergraduate degree from each country. Actual matching rates reflect the share of sample students from each country with advisors from the same undergraduate country. The top eight countries by representation are shown.

The descriptive evidence points to systematic conational matching between students and advisors. To ensure that these patterns are not simply the result of spurious correlations, such as those arising from disciplinary differences or advisor quality, we turn to regression analysis. Specifically, we estimate the following specification:

[21] This does not include the entire universe of potential advisors. Rather it only includes sample students' advisors. Insofar as either native or immigrant advisors are under-represented in this sample, we could be over- or under-estimating the predicted match rate.

[22] even accounting for the fact that faculty of Asian origin comprised 35.3 percent of tenured or tenure track computer science faculty in 2018. (See https://ira.asee.org/by-the-numbers/engineering-faculty/, last accessed 10.22.25)

$$Y_i = \beta_0 + \beta_1 Immig_i + \beta_2 prePhDpubs_i + \beta_3 preIndustryJob_i + \beta_4 advisorindustrypubs_i + \beta_5 advisorhindex_i + \delta_{gradyear} + \gamma_{institution} + \sigma_{dept} \quad (1)$$

Here, Y_i indicates the type of advisor that student i had during their PhD, which will vary across specifications. $Immig_i$ denotes an indicator variable equal to one if student i received their undergraduate degree outside of the United States (our proxy for immigrant status). In subsequent specifications, we further disaggregate immigrants into Asian LMIC immigrants and other immigrants. To account for student ability, we include $prePhDpubs_i$, the number of publications authored by student i prior to their PhD start year. To capture prior orientation toward industry, we include $preIndustryJob_i$, an indicator for whether individual i had an industry job prior to their PhD. We also control for advisor characteristics: $advisorindustrypubs_i$ counts the number of industry coauthored publications of the advisor[23] in the five years prior to their student's PhD start year, helping to rule out the possibility that industry-orientation rather than conationality is driving our result, while $advisorhindex_i$ captures advisor scholarly reputation and quality. Finally, we include fixed effects for student cohort ($\delta_{gradyear}$), PhD institution ($\gamma_{institution}$), and department (σ_{dept}). Standard errors are clustered at the level of the PhD advisor.

Regression results, presented in Table 3, corroborate the descriptive evidence. Even after accounting for student productivity, prior industry experience, advisor industry ties, advisor scholarly reputation, and a full set of fixed effects, immigrant students are 13-15 percentage points more likely than natives to have at least one immigrant advisor (columns 1-2), with Asian LMIC students being about 13 percentage points more likely than natives to be paired with an advisor who completed their undergraduate degree in an Asian LMIC country (columns 3-4). Columns 5 and 6 focus on the stricter case of exact-country matches: within the immigrant sample, Asian LMIC students are 9 percentage points more likely than other immigrants to have an advisor from their own undergraduate country. These results confirm that the matching patterns operate at the level of specific national ties.

Robustness checks further support this conclusion. The results remain similar when excluding non-science and engineering students, who may have different selection criteria for PhD programs or advisors (Appendix Table A4). Using name-inferred nationality rather than undergraduate institution-inferred nationality as an alternative measure of country of origin for the advisors provides the same qualitative results (Appendix Table A5). Controlling for the number of Asian faculty at each university[24] in the PhD start year rules out the possibility that the pattern simply reflects institutional composition (Appendix Table A6, column 2). Restricting the sample to cases where student and advisor come from different Asian countries shows no evidence of elevated matching (Appendix Table A6, column 3). Finally, excluding Chinese or Indian students, who make up the largest shares of Asian LMIC immigrants, does not eliminate the effect,

[23] In cases with more than one advisor, the maximum value is taken.
[24] Obtained from the IPEDS NCES database.

indicating that the result is not solely driven by their scale (Appendix Table A6, columns 4 and 5).

Looking from the advisor side, we observe parallel dynamics. Immigrant advisors, particularly those from Asian LMICs, are more likely to supervise immigrant students. As shown in Appendix Table B1, this pattern is concentrated among Asian LMIC advisors, who are over 20 percentage points more likely to advise Asian LMIC students and more than 30 percentage points more likely to advise students from their own undergraduate country, with no comparable tendency among other immigrant faculty. Appendix B provides supplementary evidence from both advisor-level and dyad-level analyses comparing realized advisor–student matches to the full set of feasible matches.

4.2.1 Mechanisms

The empirical results laid out above establish that immigrant students, particularly those from Asian LMIC countries, are significantly more likely to be advised by faculty from their own countries of origin. To understand the channels through which these matches are formed, we draw on survey responses and qualitative interviews with both students and advisors. This evidence points to two primary mechanisms underlying conational matching: (1) informational advantages in matching and (2) shared cultural or linguistic background. Within the first mechanism, we further distinguish three informational channels through which such advantages operate.

A first informational channel operates through advisors' evaluative capacity across educational systems. Advisors with training or professional ties to particular countries often possess deeper familiarity with local institutions, curricula, and grading norms, enabling them to more accurately interpret applicants' credentials and potential. As one advisor explained, *"International professors who are familiar with those international schools often will also hire from places where they have that deep knowledge."*

A second informational channel operates through prior contact between students and advisors. Immigrant students are more likely than natives to have prior exposure to their eventual advisors before entering the PhD program, whether through conferences, institutional visits, or shared academic networks. 60% of immigrant students reported knowing their advisor before starting their PhD, as compared to 45% of native students. Similarly, nearly 60% of immigrant advisors who supervised immigrant students also cited prior exposure to the student as a top three selection criteria, compared to just 35% of other advisors. One respondent recalled that their advisor visited their home city just once on a business trip, but that meeting was enough to establish a connection.

A third informational channel reflects reputational mediation within home-country academic networks. Asian LMIC students place greater weight on advisor reputation, with over 70% of Asian LMIC immigrant students selecting "Advisor's reputation in the field" as an important factor in advisor selection, compared to around 50% of native and other immigrants (Appendix Figure A2). Students frequently reported learning about U.S. programs and advisors through mentors in their home institutions, many of whom were themselves U.S.-trained. In this sense, advisor reputation is not globally uniform but geographically mediated, with particular faculty and departments being especially visible within specific national or regional networks. As one respondent explained, their knowledge of U.S. institutions came *"through academic mentors/advisors in my home country."*

Beyond informational advantages, shared cultural or linguistic background also appears to facilitate advisor-advisee matching and collaboration. Almost 20% of Asian LMIC immigrant students selected "shared cultural background" as particularly important in advisor choice, compared to less than 5% of native students or other immigrants. One Chinese student shared, *"My advisor was not Chinese. But many other Chinese students' advisors were. I think that one challenge was actually that we didn't share a language and culture."* Immigrant advisors echoed this theme, with one noting that *"there is a somewhat shared set of issues and concerns and language framework"* that comes from conational pairing.

4.3 Stage 2: Training and Industry Engagement

Once students enter U.S. doctoral programs, the process shifts to how they access industry-linked opportunities during training. The boundary between industry and academia has become increasingly blurred, with cross-institutional collaboration, knowledge exchange, and labor mobility now common features of the scientific enterprise (Cohen et al., 1998; Cockburn and Henderson, 1998; Bikard et al., 2019). For doctoral students, the PhD functions in part as a period of professional socialization, during which career trajectories are shaped by advisors, departments, and universities (Stephan et al., 1996; Stephan, 2012; Agarwal and Ohyama, 2013; Roach and Sauermann, 2010), and a large literature shows that advisors in particular play a central role in shaping students' exposure to industry-facing activities (Azoulay et al., 2017; Roche, 2023; Gaule and Piacentini, 2018).

In artificial intelligence, a field where the frontier of scientific knowledge and commercial application substantially overlap (Ahmed et al., 2023), doctoral students may work on problems that are simultaneously of academic and commercial relevance, using firm-supplied datasets or computational infrastructure. Relatedly, doctoral students may participate in industry-funded research, contribute to open-source software used in commercial systems, and undertake internships that double as extended job auditions. As one advisor explained, *"Companies have been quite good about having [internships], knowing that they can act indirectly as a recruiting pipeline for them"*. In this sense, doctoral students may move seamlessly between academic labs and industrial research groups.

But, access to these opportunities is not evenly distributed. Native students can draw on domestic professional networks and tacit labor market knowledge that immigrants typically lack (Granovetter, 1995; Lancee, 2013). In this context, advisor networks may therefore serve as a substitute for the professional ties that immigrant students lack (Lin et al., 2001; Kalnins and Chung, 2006; Wilson and Portes, 1980), making it important to understand which students gain exposure to industry opportunities, and through which relational channels.

In our sample, immigrant students, and in particular Asian LMIC students, undertake industry internships at a higher rate than natives, particularly at top AI firms. To further analyze these patterns of differential engagement with industry opportunities during the PhD, we estimate regression specifications of the following form:

$$Y_i = \beta_0 + \beta_1 Immig_i + \beta_2 prePhDpubs_i + \beta_3 preIndustryJob_i + \delta_{gradyear} + \gamma_{institution} + \sigma_{dept} \tag{2}$$

Here, Y_i is the outcome measure for student i, which varies across specifications but includes indicators such as undertaking an industry internship during the PhD. $Immig_i$ equals one if student i received their undergraduate degree from a non-U.S. institution (our proxy for immigrant). To account for student ability and prior professional experience, we include $prePhDpubs_i$, which is the number of publications authored by student i prior to their PhD start year, and $preIndustryJob_i$, which is an indicator for pre-PhD industry employment. Fixed effects for graduation year ($\delta_{gradyear}$), institution ($\gamma_{institution}$), and department (σ_{dept}) control for cohort, institutional, and field-level differences in opportunities for engagement with industry. Standard errors are clustered at the level of the PhD advisor. In extended specifications, we augment the model with advisor-level characteristics, such as advisors' industry coauthorships in the five years prior to the student's PhD start and advisors' h-index, to examine whether differential engagement arises through advisor-mediated opportunities.

Table 4 reports estimates of this model using internship participation as the outcome variable. The first four columns report the probability of undertaking any industry internship during the PhD, while the final four focus on internships at top AI firms. Across specifications, immigrant students are markedly more likely than U.S. natives to participate in industry internships, even after accounting for pre-PhD productivity, prior industry employment, and fixed effects for institution, department, and graduation year. Indeed, immigrant students are 18 percentage points more likely than natives to hold at least one internship during their PhD (Column 1).

Columns 2 and 6 further disaggregate immigrant by country of origin, showing that this difference is largely driven by Asian LMIC students. Asian LMIC students are roughly 22 percentage points more likely than natives to complete an internship and about 8 percentage points more likely than other immigrants to do so. The same pattern holds for prestigious industry internships: Asian LMIC students are about 14 percentage points more likely than natives to intern at top AI firms.

These differences between student groups are also mirrored in research patterns. Appendix Table A7 provides complementary evidence using publication-based measures of industry orientation. The patterns mirror those seen for internships: Asian LMIC students are more likely than natives to coauthor with industry researchers (column 2), and their average publication portfolios are 1 percentage point more "industry oriented" (column 4). These indicate differential engagement with industry-facing research environments once students enter the PhD.

4.3.1 Advisor Networks and Institutional Context

Although it may not be surprising that immigrant students engage more with industry, given their stronger industry-oriented ambitions upon entering PhD programs, advisor ties to industry seem to play a crucial role in helping them realize these goals. As seen in the descriptive statistics and in Appendix Table A8, the advisors of Asian LMIC students maintain more extensive collaborations with industry-affiliated researchers. When measures of advisor industry ties are added to the internship regressions (Columns 3 and 7 of Table 4), the Asian LMIC coefficient remains large and largely unchanged, suggesting that advisor networks do not fully account for the higher internship rates among Asian LMIC students.

However, Asian LMIC students do appear to leverage these advisor ties more intensively than other groups: the interaction between advisor industry publications and Asian LMIC status is positive and statistically significant in Columns 4 and 8 of Table 4. This is consistent with survey evidence indicating that Asian LMIC students are far more likely to report that their advisor directly facilitated an industry internship (27%, compared to 13% of other immigrants and 5% of U.S. natives; Appendix Figure A4). Together, these patterns suggest that although Asian LMIC students might enter U.S. doctoral programs with weaker independent access to domestic professional networks, they are leveraging these advisor-mediated channels to access industry opportunities during training.

The importance of advisor networks varies systematically across institutional contexts. Additional analyses, which can be found in Appendix B, suggest that advisor industry ties matter more in environments where formal university-industry pipelines are less developed, such as outside top-ten institutions and outside computer science departments. By contrast, in elite computer science programs, where formal partnerships and recruiting pipelines are common, advisor networks for immigrant students especially play a more limited role.

Taken together, these findings suggest that advisor networks serve as a key mediating infrastructure through which immigrant students, and particularly those from Asian LMIC countries, engage with industry-linked research environments during the PhD.

4.4 Stage 3: Industry Transition

In the final stage of the process, students move from doctoral training into the U.S. AI labor market. A large literature on scientific labor markets emphasizes that this sorting reflects the interaction of scientists' preferences, abilities, and institutional demand (e.g., Stern, 2004; Agarwal and Ohyama, 2013; Roach and Sauermann, 2010, 2024; Sauermann and Roach, 2012). Scientists differ in their "taste for science" (their preference for basic research and open science) versus their orientation toward applied work and higher compensation (Stern, 2004; Roach and Sauermann, 2010; Sauermann and Roach, 2012). They also vary in research abilities and in how well those abilities align with different institutional environments or are supported by advisors and departmental contexts (Agarwal and Ohyama, 2013; Azoulay et al., 2017; Roche, 2023; Gaule and Piacentini, 2018).

On the demand side, academia and industry have traditionally sought PhDs for different purposes: universities emphasize basic science and fundamental discoveries, while firms focus on applied research and commercially valuable outputs (Dasgupta and David, 1994; Stephan et al., 1996; Murray and Stern, 2007). However, in rapidly evolving fields like AI, where academic research and commercial applications are deeply intertwined (Ahmed et al., 2023), these traditional boundaries have become increasingly blurred, with industry increasingly engaging in frontier research.

For immigrant talent, these dynamics are compounded by labor-market frictions: firms hiring from global talent pools face considerable uncertainty when evaluating candidates trained in unfamiliar educational systems (Bidwell, 2011; Lancee and Bol, 2017), making it important to examine which students sort into industry and the mechanisms that shape this transition.

Our data reveal striking patterns in post-PhD employment outcomes that build on the mechanisms documented in earlier stages. Appendix Figure C1b shows the flow from students' undergraduate origins to their first post-PhD job sector. Asian LMIC graduates overwhelmingly enter industry roles, and the summary statistics from Table 2 already documented the starkness of this pattern: 70 percent of Asian LMIC students begin in industry, compared to 58 percent of other immigrants and 51 percent of U.S. natives. The same table also shows that Asian LMIC students are twice as likely as natives to begin their careers in top AI firms (51 versus 26 percent).

Likewise, Table 5, which leverages the same regression model as utilized in stage 2 (Equation 2) but with a different dependent variable (industry jobs rather than internships), demonstrates that these gaps persist even after accounting for a wide array of observable differences. Columns 1-3 estimate the probability of taking any industry job as a first placement, while Columns 4-6 focus on positions in top AI firms. Across specifications, the coefficients on immigrant student and, especially, Asian LMIC student, remain large and statistically significant. Even after controlling for pre-PhD productivity, prior industry employment, advisor characteristics, and fixed effects for department, institution, and graduation year, Asian LMIC students remain roughly 12-16 percentage points more likely than natives to take industry positions and 8-18 percentage points more likely to enter top AI firms. These results are robust to constraining the sample to U.S. stayers only (Appendix Table A9) and to the post-2016 period (Appendix Table A10). Importantly, these differences do not reflect lower academic ambition or ability: survey evidence shows no significant difference between Asian LMIC and native students in their likelihood of applying for, or receiving, academic job offers (Figure A5).

The concentration of immigrants in industry, and particularly in top AI firms, could reflect many factors beyond what accumulates during the PhD: differences in language or teaching skills that favor natives in academia, heterogeneous preferences or talents across groups, visa-related constraints that make academic pathways riskier for international graduates, or selection effects whereby migrants are drawn from the right tail of the talent distribution (e.g., Borjas, 1987; Peri and Sparber, 2009; Bahar et al., 2024; Moser et al., 2014).

At the same time, career trajectories are not likely to be shaped by structural barriers or preferences alone. Experiences gained during the PhD could also play a role in channeling immigrant talent into U.S. firms.

4.4.1 Internships as a Hinge to Elite Industry Employment

Industry internships appear to play a decisive role in structuring post-PhD outcomes, especially for immigrant students. In our description of Stage 2, we showed that Asian LMIC students are substantially more likely than both natives and other immigrants to undertake internships, and especially internships at top AI firms. Columns 3 and 6 of Table 5 indicate that internship participation is strongly associated with beginning one's career in industry, even after accounting for pre-PhD productivity, advisor characteristics, and prior industry exposure.

The internship-to-job link is particularly salient for Asian LMIC students. Among those employed at top AI firms, only 39% of Asian LMIC immigrants reached these positions without prior internships, compared to 50% among all other groups. This suggests that internships are a more common, and perhaps more necessary, route into elite firms for this group, whether due to visa constraints, greater reliance on faculty networks, or the signaling value of prior firm-based experience. Appendix Table A11 shows that the association between internships and top AI firm employment holds across university ranks but is somewhat stronger for students outside computer science departments. This complements the Stage 2 finding that advisor networks matter more for internship access in these same settings (Appendix Table B3). Interview evidence helps explain why: at top-ranked CS programs, formalized recruiting partnerships between departments and leading firms provide structured access to internships regardless of individual advisor connections, whereas in programs without such institutional pipelines, students depend more heavily on advisor-mediated channels. These patterns are also consistent with a firm-side logic: internships plausibly function as a screening mechanism that reduces the 'information impactedness' (Bidwell and Keller, 2014) associated with evaluating candidates from unfamiliar training environments, allowing firms to observe capabilities firsthand rather than relying solely on credentials that are difficult to interpret across borders.

Appendix Figure C2 visually reinforces this hinge mechanism: students from Asian LMIC countries display the highest rates of internship participation and the strongest flows into industry roles. Among Asian LMIC students who secured internships, a large share transition directly into industry positions, whereas those without internships are more likely to enter academia.

Qualitative accounts suggest that internships function as important experiences that reshape students' understanding of industry possibilities. One immigrant respondent explained how the internship experience shifted their orientation from academia toward industry: *"when I did that internship, I enjoyed the experience, but also my mentors there told me a bit more about what the differences are. In particular, they talked about how they were able to do research without having to apply for grants and funding and worry about those things... I had this fear that if I was to go to a company then I would be working on whatever product the company was making, and they assured me that no, that's not necessary. You can also to blue sky research"*. Another immigrant student described their trajectory as follows: *"I started out thinking I'd definitely be a researcher in academia, and over the course of two industrial research internships became increasingly interested in industrial research opportunities."* These accounts reinforce the hinge function of internships: they connect prior doctoral engagement to post-graduation career decisions by providing direct experience that can reshape students' perceptions of what industry careers entail.

Beyond facilitating internships, advisors also appear to play a broader sponsorship role for immigrant students at the job search stage. Survey evidence shows that over 40% of Asian LMIC students reported that their advisor played a significant role in shaping their post-PhD career decisions, compared to roughly 30% of U.S. natives and other immigrants (Appendix Figure A3). This elevated advisor influence likely reflects both the informational advantages that advisors provide and the greater uncertainty immigrant students face when navigating unfamiliar labor markets. Interview data further illustrate this dynamic. One immigrant student explained: *"my advisor was also an entrepreneur who made it clear that that was a viable and potentially impactful path and made introductions to encourage this route when I told him I was interested."* Another noted the importance of advisor attitudes: *"many advisors do not encourage industry careers. My advisor encouraged it and allowed me to take courses outside the department to support my pursuit of an industry career."* These patterns suggest that advisor sponsorship operates as a late-stage mechanism that helps translate industry exposure into concrete employment outcomes, particularly for students who may have less independent access to professional networks in the United States.

5 Discussion

This paper develops a process-oriented account of how U.S. universities serve as institutional intermediaries that resolve the challenges separating global AI talent from U.S. frontier firms. By tracing how immigrant researchers enter, navigate, and move beyond U.S. doctoral programs, we identify the specific relational structures (diaspora faculty, advisor-industry networks, and internship pipelines) that support the transition of global talent into elite U.S. AI firms.

A process perspective is particularly useful in this setting because it allows us to trace how relational structures shape selective access to U.S. doctoral training and, over time, generate concentrated employment outcomes. In the global AI labor market, strong economic push–pull forces, visa constraints, and interest in industry careers affect highly skilled individuals across many countries, making U.S. university PhD programs attractive entry points into the labor market. These forces alone, however, do not explain how immigrants overcome significant challenges in their journey from home countries into U.S. institutions and into the labor market. For example: immigrants face information asymmetries in applying to, and joining U.S. university programs, immigrants often lack the domestic professional networks through which opportunities flow, and employers may face uncertainty when screening candidates from unfamiliar training environments. Nor do they explain which countries' students actually gain access to U.S. doctoral training or why particular national groups come to dominate subsequent stages of the pipeline.

Our findings from our process model highlight the sequential ways in which relational structures shape immigrant students' experiences across the doctoral pipeline. In the first stage, immigrant students, particularly those from Asian LMIC countries, tend to be matched with faculty from their home countries, suggesting that conational ties may help reduce uncertainty when navigating unfamiliar programs and advisors. During the second stage, immigrant students, particularly those from Asian LMIC countries, engage more intensively with industry-linked research environments, often through advisor-facilitated internships, indicating that advisor networks can help compensate for limited professional connections and labor-market knowledge. Finally, in the transition to employment, internships emerge as an important pathway for immigrants into top AI firms, providing students with experience while giving firms a way to evaluate candidates whose credentials are otherwise difficult to interpret.

Connecting the process model to the literature. Our findings draw upon and connect to several literatures, including those on coethnic clustering, doctoral influence, and scientific labor markets.

Prior research on ethnic networks and social capital (Freeman and Huang, 2015; Kalnins and Chung, 2006; Kerr and Mandorff, 2023; Marinoni, 2023; Nanda and Khanna, 2010; Åslund et al., 2014; Kerr and Kerr, 2021) emphasizes how coethnic or conational ties transmit information, trust, and opportunities when formal signals are incomplete. Our evidence shows similar dynamics in doctoral admissions and mentorship: conational ties create clustering of students and advisors, and our survey evidence points to the idea that diaspora faculty reduce the uncertainty surrounding heterogeneous foreign credentials, interpret academic signals from abroad, and serve as transnational brokers linking origin-country institutions to U.S. universities.

A long line of research emphasizes that doctoral training is both an educational and a labor market process: it socializes scientists into distinct professional roles and channels them toward organizations where their skills, preferences, and opportunities align (Stephan et al., 1996; Stephan, 2012; Agarwal and Ohyama, 2013; Roach and Sauermann, 2010), and in particular, research on doctoral advising shows that advisors shape students' orientations, opportunities, and professional identities (Azoulay et al., 2017; Roche, 2023; Gaule and Piacentini, 2018). In AI, where industry and academic research are deeply intertwined (Ahmed et al., 2023), advisors with industry relationships are well positioned to secure internships for their students, introduce them to industry partners, and involve them in collaborative projects. Our data show that while immigrant students are more likely to enter into elite industry jobs post-PhD, they are also the group that particularly benefit from these relational channels, and they are especially likely to leverage both advisor ties and internships during their PhDs.

While immigrants in our sample are more predisposed to entering into industry even prior to the PhD, entry isn't automatic. These advisor- and internship-based channels appear to be especially consequential for immigrant students because they help compensate for several challenges that immigrants face even after they are enrolled in a U.S. PhD program. First, immigrants face the liability of foreignness in host countries (Zaheer, 2017); they might lack the embedded professional networks, prior U.S. work experience, and informal knowledge that native students often possess. Second, firms may face greater uncertainty when evaluating immigrant candidates, given the difficulty of interpreting credentials and prior training across borders, a form of "information impactedness" highlighted in research on external labor markets (e.g., Bidwell and Keller, 2014). Internships may allow firms to internalize candidate evaluation, reducing uncertainty that may surround immigrant potential hires, especially in comparison to natives, that might otherwise deter external hiring. Consistent with this, the internship pathway is more consequential in settings where formalized recruiting pipelines are less developed, suggesting that advisor-mediated channels substitute for institutional ones when the latter are unavailable. Advisor relationships further help firms interpret student capabilities and potential. Together, these mechanisms can reduce hiring frictions for firms while providing immigrants with pathways into elite industry roles.

This paper makes several contributions. The primary contribution of this paper is to show that the movement of skilled immigrant scientists into U.S. frontier firms is structured by institutional intermediation, rather than arising straightforwardly from economic incentives, preferences, or labor market sorting. The migration literature emphasizes how economic incentives and migration costs shape self-selection and destination choice (e.g. Borjas, 1987; Grogger and Hanson, 2011), and research on high-skill immigration documents immigrants' disproportionate contributions to innovation and firm performance (e.g., Stephan and Levin, 2001; Beerli et al., 2021; Brinatti et al., 2023; Glennon et al., 2025; Hunt, 2011; Bernstein et al., 2022). But these literatures typically treat the supply of immigrant talent as exogenous to firms, offering limited insight into how immigrants come to be hired in the first place. We fill this gap by identifying the specific relational structures through which universities channel global talent into a small set of top firms, and in doing so, resolving challenges that operate on both sides of the market.

Much of the existing literature implicitly adopts a "talent will surface" assumption: that exceptional individuals will naturally be identified by employers, and that matching is driven primarily by firms' search efforts and workers' preferences. This view imagines a world in which, if one is a remarkable coder, it is only a matter of time before they are found by a top firm. But in reality, talent rarely "just appears." The distance between global talent pools and frontier firms is vast, shaped by asymmetric information, heterogeneous credentials, visa restrictions, and the institutional complexity of scientific labor markets. Our process perspective demonstrates these complexities.

In developing this account, we also contribute to research on hiring and talent pipelines (e.g., Brymer et al., 2014, 2019; Josefy et al., 2022) by showing how universities serve as upstream labor-market infrastructure that is especially consequential for immigrant scientists. For immigrants, these university-mediated structures substitute for host-country networks and institutional knowledge that native students more often possess, making academic pipelines especially consequential for immigrant career outcomes.

Lastly, our results also extend the large literature on scientific labor markets which considers the factors driving the choice between industry and academia (e.g., Stern, 2004; Agarwal and Ohyama, 2013; Roach and Sauermann, 2010, 2024; Sauermann and Roach, 2012). This literature emphasizes the roles of preferences, perceived fit, compensation, and exposure to industry opportunities in shaping career outcomes. Our findings complement and extend this work by showing that such sorting is not simply the result of stable preferences or contemporaneous labor-market conditions, but emerges from a cumulative sequence of institutional and relational mechanisms operating during doctoral training. In particular, we show that early access to industry-linked research environments, internships, and advisor-mediated networks shapes the opportunity sets within which career decisions are made, and that these mechanisms are especially consequential for immigrant scientists who face greater uncertainty and weaker host-country embeddedness. As a result, transitions into industry reflect not only differences in tastes or abilities, but also differential exposure, feasibility, and screening that accrue over the course of training.

Implications for Policy and Practice. The patterns we document reveal a structural vulnerability in how frontier AI firms access talent. Because the university's intermediating function depends on specific relational structures rather than on the institution as a monolithic entity, the pipeline is fragile to targeted disruptions that may break individual stages even as the university itself continues to operate.

The vulnerability begins with the legal infrastructure that makes the pipeline possible in the first place. Student visas and post-graduation work authorization (OPT) are not part of the intermediation process itself, but they are the precondition on which it rests. Restrictions on student visa issuance or reductions in OPT duration would narrow the pipeline at its origin, before any of the university's relational structures can operate. Beyond legal access, each stage of the intermediation process has its own point of fragility. Limitations on the hiring or retention of immigrant faculty, whether through visa restrictions, funding constraints, or political pressures, diminish the diaspora networks that resolve informational asymmetries at the point of entry (Stage 1). Reductions in faculty-industry collaboration limit the advisor networks through which immigrant students disproportionately access internships and industry engagement during training (Stage 2). And disruptions to university-industry partnerships more broadly constrain the internship and screening channels through which firms resolve uncertainty about foreign-trained candidates (Stage 3). Each of these disruptions targets a distinct relational structure, and each can degrade the pipeline independently.

For firms, these findings underscore that access to global AI talent is shaped not solely by labor market dynamics but by the upstream functioning of universities and their faculty networks. Hiring pipelines operating through internships rely heavily on the strength of advisor ties to industry and on the presence of diaspora faculty who are positioned to identify, recruit, and mentor immigrant students. Firms that depend on this talent should recognize that their access to it is contingent on institutional arrangements upstream of their own hiring processes, arrangements that are currently under pressure at multiple points.

These results also speak to ongoing debates about immigration policy. Recent efforts to limit student visas, restrict or deport international students and scholars, or reduce pathways to permanent residence may have downstream consequences for the U.S. innovation economy. Our findings suggest that U.S. Ph.D. programs constitute a critical entry point through which foreign-born scientists access high-skill employment in the United States. Constraints on the flow of international students or faculty are likely to disrupt not only the supply of talent but also the functioning of the pipeline itself.

Moreover, immigration policies that increase uncertainty, such as instability in the F-1 or H-1B regimes, may alter incentives for prospective students. Interviews suggested that these dynamics are already becoming salient. One interviewee noted that he now cautions prospective students in India *"not to come to the U.S. unless they intend to return"*, reflecting rising concerns about the feasibility of staying after graduation. To the extent that these perceptions become widespread, they may reduce the inflow of global AI talent and redirect skilled individuals to other innovation hubs.

Taken together, our results highlight that interventions aimed at shaping the U.S. AI workforce cannot focus solely on firm-side hiring practices or university admissions policies. Instead, they must attend to the interdependencies across stages of the global-to-U.S. talent pipeline. Policies that support international student enrollment, sustain the ability of immigrant faculty to advise and collaborate, and maintain stable visa transitions at graduation are likely to have outsized effects on the functioning of this pipeline.

Boundary Conditions and Generalizability. Our study focuses on a narrow setting: immigrant Ph.D. graduates of top U.S. programs studying AI-related topics. On the one hand, many of the mechanisms we identify are likely to extend to other domains: conational advising relationships, reputational pipelines from sending countries, and advisor-mediated access to internships are not unique to AI. On the other hand, AI has several features that make the dynamics we document particularly visible: it is a fast-moving field at the technological frontier with deep integration between academic and industry research and unusually high demand for talent across both sectors. Moreover, the resource-intensive nature of modern AI research, such as the need for large-scale computing infrastructure, makes industry employment particularly attractive, especially relative to more resource-constrained academic environments. These features may amplify the dynamics we report here. For example, the role of advisor influence on career outcomes and conational matching may be more salient in this context, as shared networks and prior contact may help navigate a complex and competitive landscape.

Our focus on top doctoral programs also has implications for how these mechanisms may operate elsewhere. Outside elite institutions, where formal university–industry pipelines and strong institutional reputations are less developed, advisor networks and internships may play an even more central role in mediating access to industry opportunities. In such settings, firms may rely more heavily on relational screening and prior collaboration to evaluate candidates, potentially increasing the importance of advisor sponsorship and internship-based pathways, particularly for immigrant students. At the same time, weaker institutional signals may limit access to frontier firms for graduates of lower-ranked programs, suggesting that the processes we document could operate with different intensity.

Our sample covers graduates from 2014 to 2018, a period of rapid but relatively stable growth in the U.S. AI sector. Since then, the landscape has shifted considerably: the post-2022 generative AI boom dramatically increased industry demand for PhD-trained researchers, immigration policy has become more uncertain, and geopolitical tensions have introduced new frictions into U.S.-China scientific exchange. These changes likely affect the magnitudes we estimate. For instance, intensified industry demand may have strengthened the internship-to-hiring pathway, while visa uncertainty may have weakened the pipeline's ability to attract entrants in the first place. The core mechanisms we identify, however, operate through relational structures that predate these shifts and are not specific to any particular market cycle.

That said, the mechanisms we uncover are likely to apply in other settings where immigrants are navigating opaque or high-stakes professional environments. In disciplines with lower demand for Ph.D.s in industry, or less international student presence, advisor influence may still be meaningful, but the pathways may differ. For example, in fields such as history or mathematics, where industry options are more limited, conational matching may shape trajectories more through academic network access or informal support than through industry internship facilitation. Our findings are therefore most likely to generalize to STEM fields, especially those undergoing rapid change or where the public-private boundary is blurred, but the specific institutional context of AI should be kept in mind when considering broader implications. Future work should examine how these dynamics unfold across other programs and fields.

Finally, it's important to note that our results should be interpreted as correlations, none of the findings are causal, and we are unable to infer the proportion of immigrant to non-immigrant scientists in U.S. PhD programs, or elite AI firms that is optimal. We encourage future work that investigates the causal relationships between components of the pathway we describe and outcomes.

Conclusion. By conceptualizing the global-to-U.S. AI talent pipeline as a temporally ordered sequence of interconnected mechanisms, this paper reframes skilled migration and doctoral training as dynamic, cumulative processes. The stages we identify demonstrate how relational structures at successive points in doctoral training shape the opportunities through which immigrant talent reaches U.S. frontier firms. In doing so, we offer a theoretically grounded account of how global AI talent is channeled into U.S. frontier firms.

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Table 1: Graduating Institution for Study Sample AI Students

	N	Native %	Asian LMIC %	Other Immigrant %
Overall	1,757	0.48	0.30	0.22
Institution				
California Institute of Technology	14	0.29	0.21	0.50
Carnegie Mellon University	53	0.38	0.38	0.24
Columbia University	80	0.50	0.31	0.19
Cornell University	64	0.52	0.28	0.20
Georgia Institute of Technology	60	0.43	0.37	0.20
Harvard University	29	0.55	0.14	0.31
Massachusetts Institute of Technology	174	0.58	0.12	0.30
Princeton University	62	0.52	0.31	0.17
Stanford University	193	0.64	0.17	0.19
The University of Texas at Austin	9	0.33	0.33	0.33
The University of Wisconsin - Madison	69	0.42	0.43	0.15
University of California, Berkeley	154	0.58	0.21	0.21
University of California, Los Angeles	64	0.38	0.41	0.21
University of Illinois	97	0.31	0.40	0.29
University of Maryland, College Park	131	0.32	0.47	0.21
University of Massachusetts Amherst	129	0.53	0.32	0.22
University of Michigan	77	0.44	0.37	0.19
University of Pennsylvania	70	0.54	0.26	0.20
University of Southern California	96	0.19	0.51	0.30
University of Washington	132	0.58	0.22	0.20
Department				
Biology	40	0.68	0.10	0.23
Chemistry	26	0.77	0.15	0.08
Computer Science	406	0.42	0.37	0.21
Engineering	782	0.40	0.34	0.26
Environmental Science	4	0.25	0	0.75
Geology	11	0.82	0.09	0.09
Materials Science	16	0.50	0.19	0.31
Mathematics	146	0.53	0.31	0.16
Medicine	85	0.71	0.12	0.17
Physics	39	0.62	0.23	0.15
Other Non-S&E	202	0.63	0.14	0.23
Post-Graduation First Employer				
Google	127	0.32	0.45	0.23
Facebook	66	0.33	0.55	0.12
Microsoft	55	0.36	0.38	0.26
Stanford University	45	0.49	0.36	0.15
Amazon	40	0.25	0.53	0.22
Princeton University	23	0.52	0.17	0.31
Apple	23	0.22	0.30	0.48
Massachusetts Institute of Technology	22	0.45	0.18	0.37
Harvard University	21	0.57	0.14	0.29
IBM	21	0.52	0.24	0.24

Notes: The underlying data are from CSET and consist of 1,757 artificial intelligence PhD students from the top twenty U.S. institutions. Column 1 (N) is the count of sample students in each category. Column 2 (Native %) is the percentage of sample students who completed their undergraduate education in the United States. Column 3 (Asian LMIC %) is the percentage of sample students who completed their undergraduate education in Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka, or Vietnam. Column 4 (Other Immigrant %) is the percentage of sample students who completed their undergraduate education in any other non-U.S. country.

Table 2: Summary Statistics for Study Sample AI Students - Mean (Std Dev)

	Native	Asian LMIC	Other Immigrant
N	839	522	396
PhD graduation year	2016 (1.41)	2016 (1.38)	2016 (1.37)
Top 10 PhD institution	0.64 (0.48)	0.47 (0.50)	0.58 (0.49)
Pre-PhD graduation number of publications	4.37 (7.69)	8.29 (10.25)	5.80 (8.49)
Any immigrant advisor	0.33 (0.47)	0.53 (0.50)	0.53 (0.50)
Maximum advisor industry collaborative publications	4.97 (8.03)	8.54 (11.42)	6.53 (9.41)
Industry internship during PhD	0.27 (0.44)	0.55 (0.50)	0.43 (0.50)
Industry internship in top AI firm during PhD	0.18 (0.38)	0.35 (0.48)	0.26 (0.44)
Work in U.S. post PhD graduation	0.94 (0.23)	0.95 (0.22)	0.87 (0.34)
First job industry	0.51 (0.50)	0.70 (0.46)	0.58 (0.49)
First job top AI industry employer	0.26 (0.44)	0.51 (0.50)	0.38 (0.49)
First job academia	0.43 (0.50)	0.29 (0.45)	0.38 (0.49)

Notes: This sample consists of 1,757 artificial intelligence U.S. PhD students. Natives are those with U.S. undergraduate locations. Asian LMIC include those with undergraduate degrees from Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka, or Vietnam. Other immigrant students are all other non-U.S. undergraduate locations. Pre-PhD graduation publications are those authored by the student during the PhD time. Maximum advisor industry collaborative publications are the maximum of all advisors (if the student has more than one advisor) publications coauthored with industry affiliated researchers, measured in the five years prior to the PhD start year. Top AI employers are the 22 U.S. firms that are top valued on the stock market or rated as top employers in 2018 by Forbes and Business Insider.

Table 3: Immigrant Students and Diaspora Advisors

	Advisor with Non-U.S. Undergraduate		Advisor with LMIC Asian Country Undergraduate		Advisor With Same Undergraduate Country, Just Immigrant Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant student	0.1528***	0.1359***				
	(0.026)	(0.026)				
Asian LMIC student			0.1326***	0.1231***	0.0833***	0.0875***
			(0.024)	(0.023)	(0.027)	(0.027)
Other immigrant student			0.0370*	0.0262		
			(0.020)	(0.020)		
Total Observations	1757	1757	1757	1757	918	918
Mean of Dep. Variable	0.4371	0.4371	0.1537	0.1537	0.1503	0.1503
Graduation Year FE	X	X	X	X	X	X
PhD Department FE	X	X	X	X	X	X
PhD Institution FE	X	X	X	X	X	X
Pre-PhD Publications		X		X		X
Pre-PhD Industry Job		X		X		X
Advisor Industry Publications		X		X		X
Advisor H-index		X		X		X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: [a] Estimates stem from OLS regression in which dependent variables are dummy outcomes. Immigrant students are those with non-U.S. undergraduates. Asian LMIC students include those with undergraduate degrees from Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka, or Vietnam. Other immigrant students are those from all other non-U.S. undergraduate locations. Columns 1-2 report the likelihood of having at least one non-U.S. educated advisor. Columns 3-4 report the likelihood of having at least one advisor educated in an Asian LMIC country. Columns 5-6 report the likelihood of sharing the same undergraduate country as an advisor (restricted to the immigrant student sample). Odd-numbered columns include institution, department, and graduation year fixed effects, while even-numbered columns add student and advisor controls. [b] Heteroskedastic robust standard errors clustered at the level of the advisor are given in parentheses.

Table 4: Industry Internships

	Industry Internship During PhD				Top Industry Internship During PhD			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigrant student	0.1798***				0.1102***			
	(0.023)				(0.020)			
Asian LMIC student		0.2166***	0.2058***	0.1201***		0.1438***	0.1389***	0.0592
		(0.028)	(0.028)	(0.046)		(0.025)	(0.025)	(0.039)
Other immigrant student		0.1377***	0.1357***	0.0843**		0.0717***	0.0714***	0.0495
		(0.028)	(0.027)	(0.041)		(0.024)	(0.024)	(0.035)
Advisor Industry Pubs			0.0457***	0.0212			0.0208**	0.0020
			(0.010)	(0.013)			(0.009)	(0.011)
Advisor Industry Pubs × Asian LMIC student				0.0474**				0.0431**
				(0.020)				(0.017)
Advisor Industry Pubs × Other immigrant student				0.0317				0.0145
				(0.021)				(0.018)
Total Observations	1757	1757	1757	1757	1757	1757	1757	1757
Mean of Dep. Variable	0.3899	0.3899	0.3899	0.3899	0.2482	0.2482	0.2482	0.2482
Year FE	X	X	X	X	X	X	X	X
Department FE	X	X	X	X	X	X	X	X
Institution FE	X	X	X	X	X	X	X	X
Pre-PhD Industry Job	X	X	X	X	X	X	X	X
Pre-PhD Publications	X	X	X	X	X	X	X	X
Advisor H-index			X	X			X	X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: [a] Estimates stem from OLS regression in which dependent variables are dummy outcomes. Immigrant students are those with non-U.S. undergraduates. Asian LMIC students are those completing undergraduate education in Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka or Vietnam. Other immigrant students are all other non-U.S. undergraduate locations. Columns 1-4 report the likelihood of undertaking an industry internship during the PhD. Columns 5-8 report the likelihood of undertaking an industry internship in a top AI firm during the PhD. Advisor industry pubs are the sum of the advisors' (or maximum in the case of multiple advisors per student) publications coauthored with industry affiliated researchers in the five years prior to the PhD start year. Top AI employers are 22 U.S. firms that are top valued on the stock market, or rated as employers in 2018 by Forbes and Business Insider. [b] Heteroskedastic robust standard errors clustered at the level of the advisor are given in parentheses.

Table 5: Careers

	Industry Job Post PhD			Top Industry Job Post PhD		
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant student	0.1077***			0.1393***		
	(0.025)			(0.022)		
Asian LMIC student		0.1556***	0.1187***		0.1814***	0.0825***
		(0.029)	(0.029)		(0.027)	(0.020)
Other immigrant student		0.0430	0.0164		0.0919***	0.0403**
		(0.031)	(0.030)		(0.027)	(0.019)
Industry internship			0.2199***			
			(0.026)			
Top industry internship						0.7530***
						(0.019)
Total Observations	1757	1757	1757	1757	1757	1757
Mean of Dep. Variable	0.5834	0.5834	0.5834	0.3597	0.3597	0.3597
Year FE	X	X	X	X	X	X
Department FE	X	X	X	X	X	X
Institution FE	X	X	X	X	X	X
Pre-PhD Industry Job	X	X	X	X	X	X
Pre-PhD Publications	X	X	X	X	X	X
During-PhD Publications	X	X	X	X	X	X
Advisor Industry Publications	X	X	X	X	X	X
Advisor H-index	X	X	X	X	X	X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

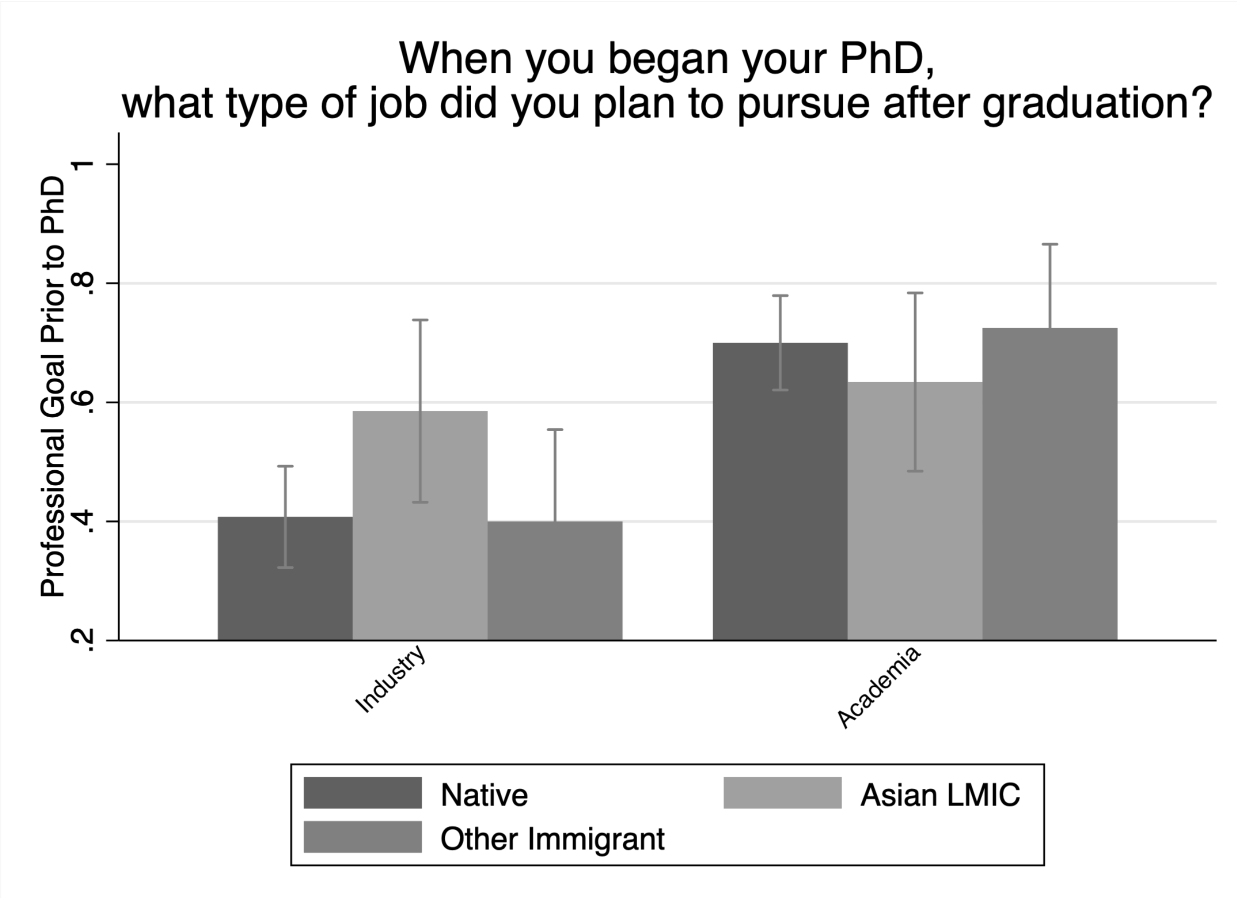
Notes: [a] Estimates stem from OLS regression in which dependent variables are dummy outcomes. Immigrant students are those with non-U.S. undergraduates. Asian LMIC students are those completing undergraduate education in Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka or Vietnam. Other immigrant students are all other non-U.S. undergraduate locations. Columns 1-3 report the likelihood of having an industry job as the first job post-PhD. Columns 4-6 report the likelihood of having a top AI job as the first job post PhD. Top AI employers are 22 U.S. firms that are top valued on the stock market, or rated as employers in 2018 by Forbes and Business Insider. [b] Heteroskedastic robust standard errors clustered at the level of the advisor are given in parentheses.

ONLINE APPENDIX FOR: MAPPING THE INSTITUTIONAL PIPELINE FOR GLOBAL AI TALENT

March 14, 2026

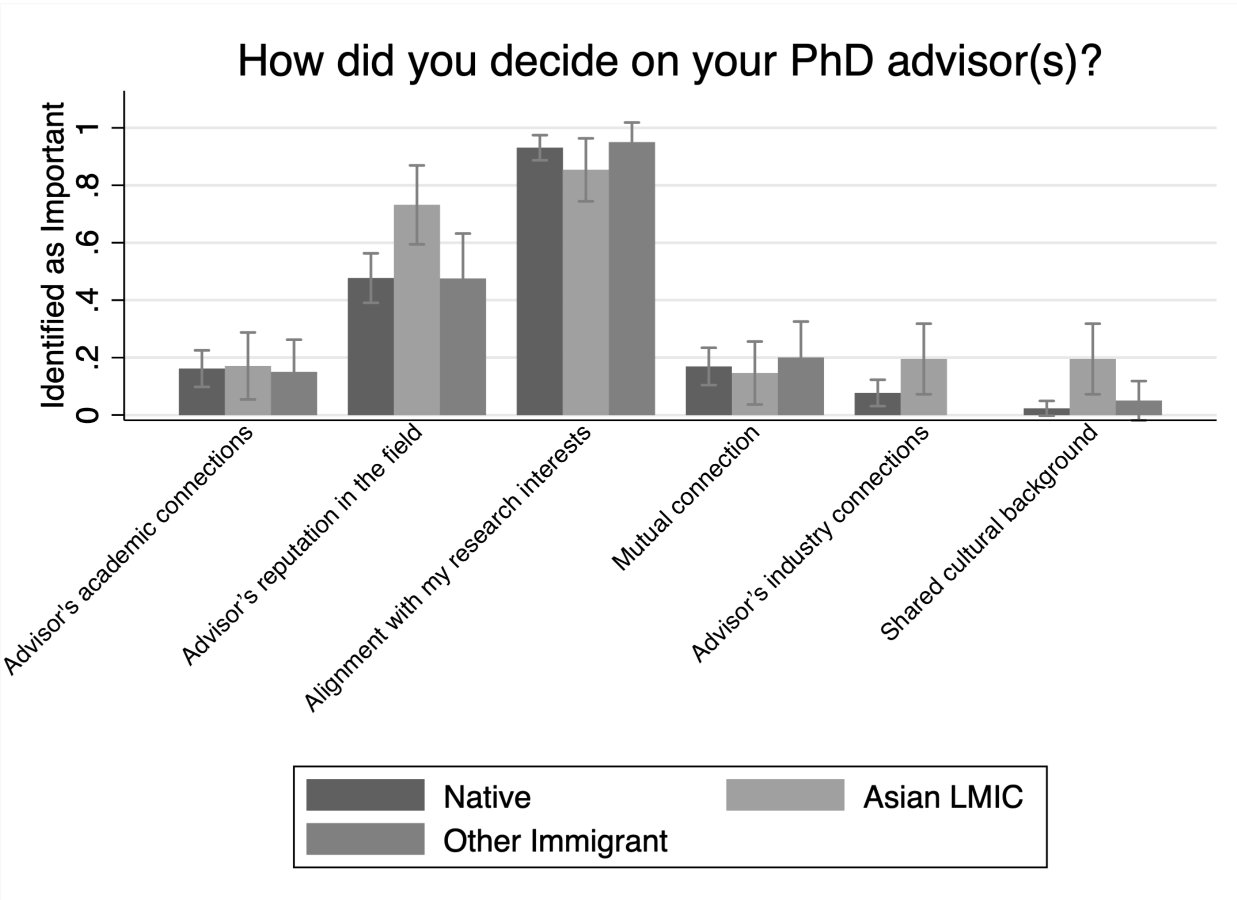
A Appendix A

Figure A1: Pre-PhD Professional Goals



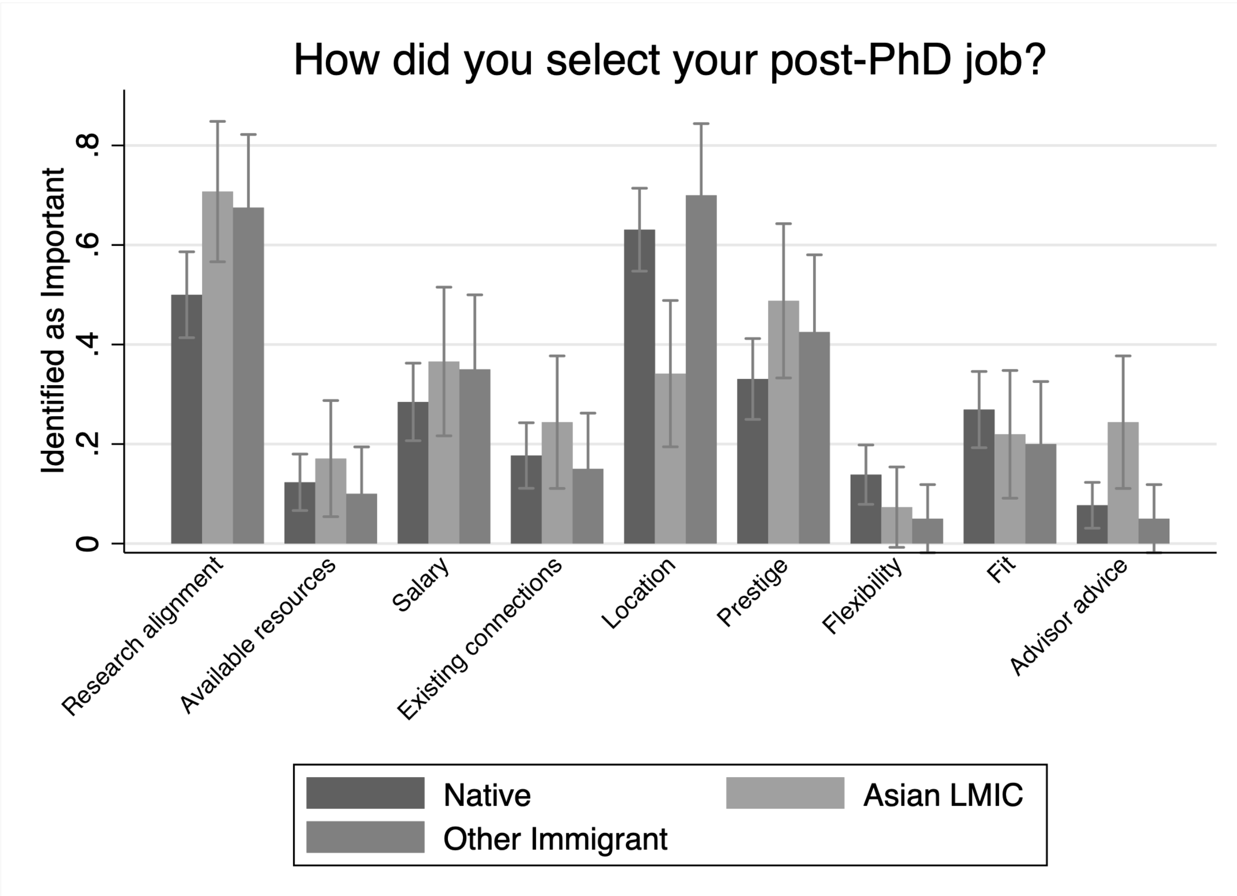
Notes: We asked students: When you began your PhD, what type of job did you plan to pursue after graduation? (Select all that apply. If you didn't have a preference select both). They chose from: Industry (e.g., tech companies); Academia; Other (please specify). For each option, we plot the average share of respondents who selected it (coded as 1 if selected, 0 otherwise), with averages and confidence intervals shown separately for each group of survey respondents. Native are those completing undergraduate education in the U.S.. Asian LMIC students are those completing undergraduate education in Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka, or Vietnam. Other immigrants are all other non-U.S. undergraduate locations.

Figure A2: Advisor Selection Criteria



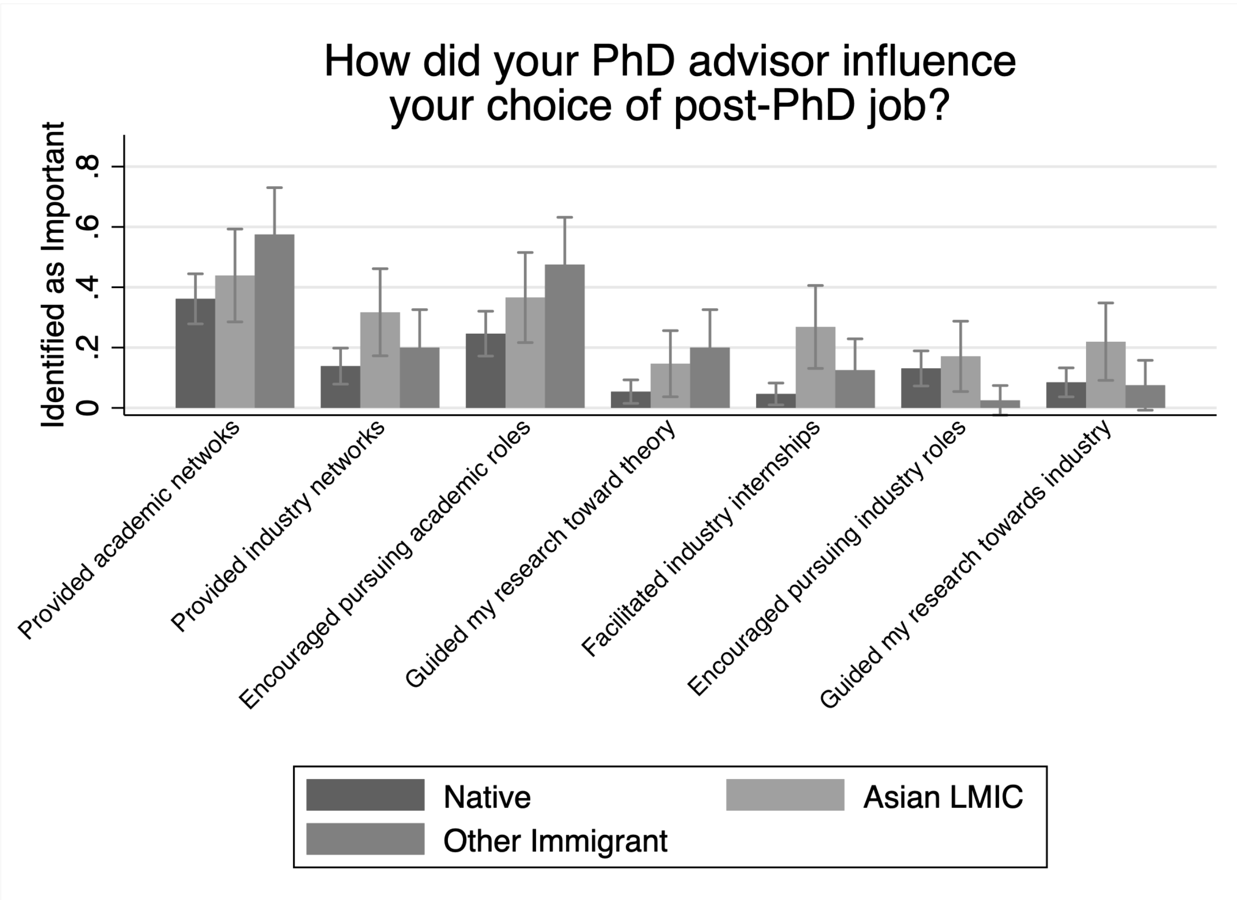
Notes: Ph.D. students were asked: How did you decide on your Ph.D. advisor(s)? Please select the top (up to) three most important factors. They chose from: Shared cultural background, cultural familiarity, or language considerations (if applicable); Advisor's industry connections (e.g., relationships with companies, potential for internships or post-Ph.D. positions); Advisor's academic connections (e.g., collaborations with other researchers, access to prestigious networks); Advisor's reputation in the field (e.g., prominence, citation impact); Mutual connection or shared professional network; Alignment with my research interests (e.g., expertise in my area of focus). For each option, we plot the average share of respondents who selected it (coded as 1 if selected, 0 otherwise), with averages and confidence intervals shown separately for each group of survey respondents. Native are those completing undergraduate education in the U.S.. Asian LMIC students are those completing undergraduate education in Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka, or Vietnam. Other immigrants are all other non-U.S. undergraduate locations.

Figure A3: Job Selection Criteria



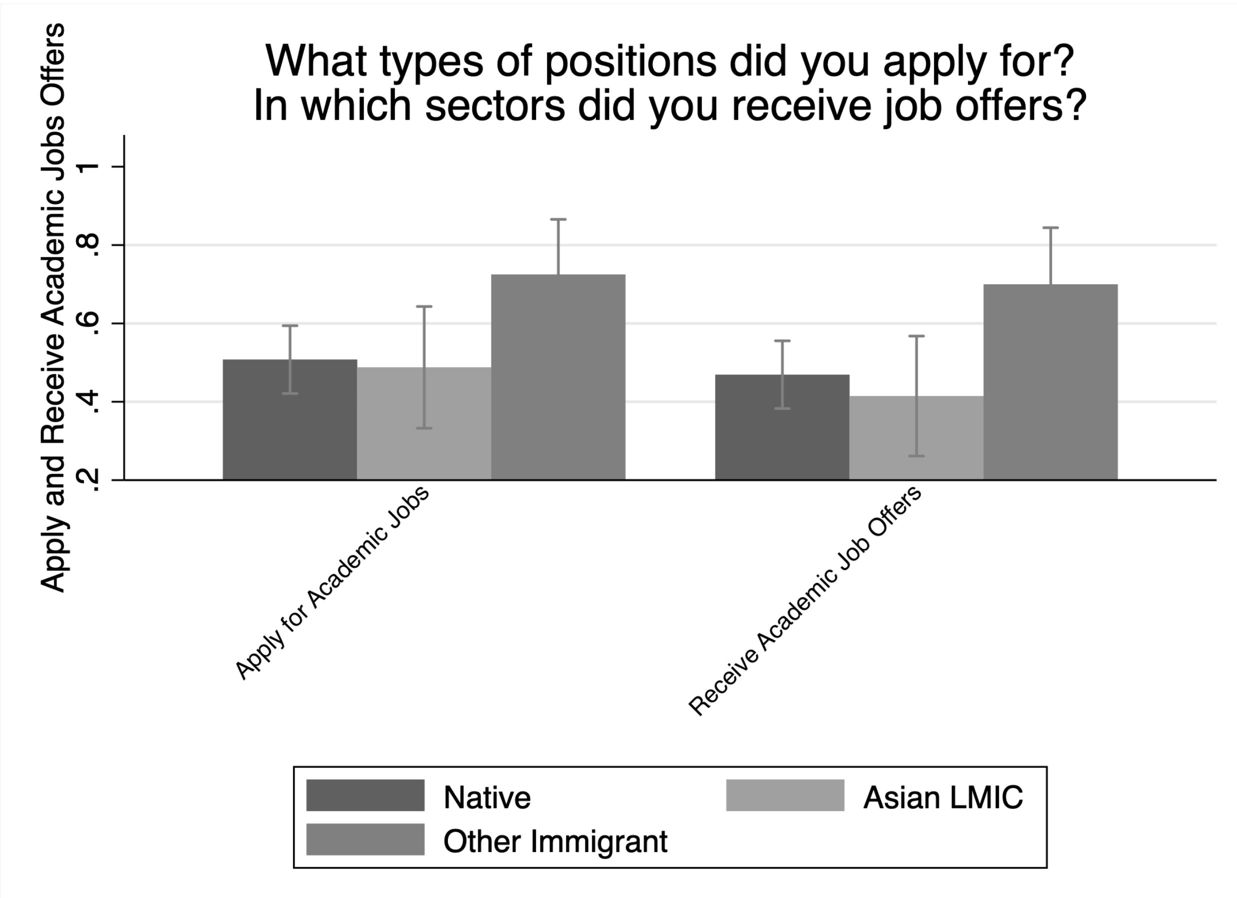
Notes: Students were asked: Please select the top (up to) three most important factors for choosing your first job after your PhD. They selected from: Alignment with my research interests or topical fit; Available resources (e.g., funding, access to facilities, research support, computing power); Salary; Existing connections or relationships with the organization (e.g., internship experience, coauthors); Location of the position (e.g., proximity to family, cost of living); Prestige of the position (e.g., academic reputation, industry visibility); Flexibility of position (e.g., remote work options, work-life balance, adaptable schedules, multiple offices)'; Fit with the professional environment (e.g., organizational culture, team dynamics, creative independence); Advice from my advisor. For each option, we plot the average share of respondents who selected it (coded as 1 if selected, 0 otherwise), with averages and confidence intervals shown separately for each group of survey respondents. Native are those completing undergraduate education in the U.S.. Asian LMIC students are those completing undergraduate education in Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka, or Vietnam. Other immigrants are all other non-U.S. undergraduate locations.

Figure A4: Advisor Influence on Career Pathways



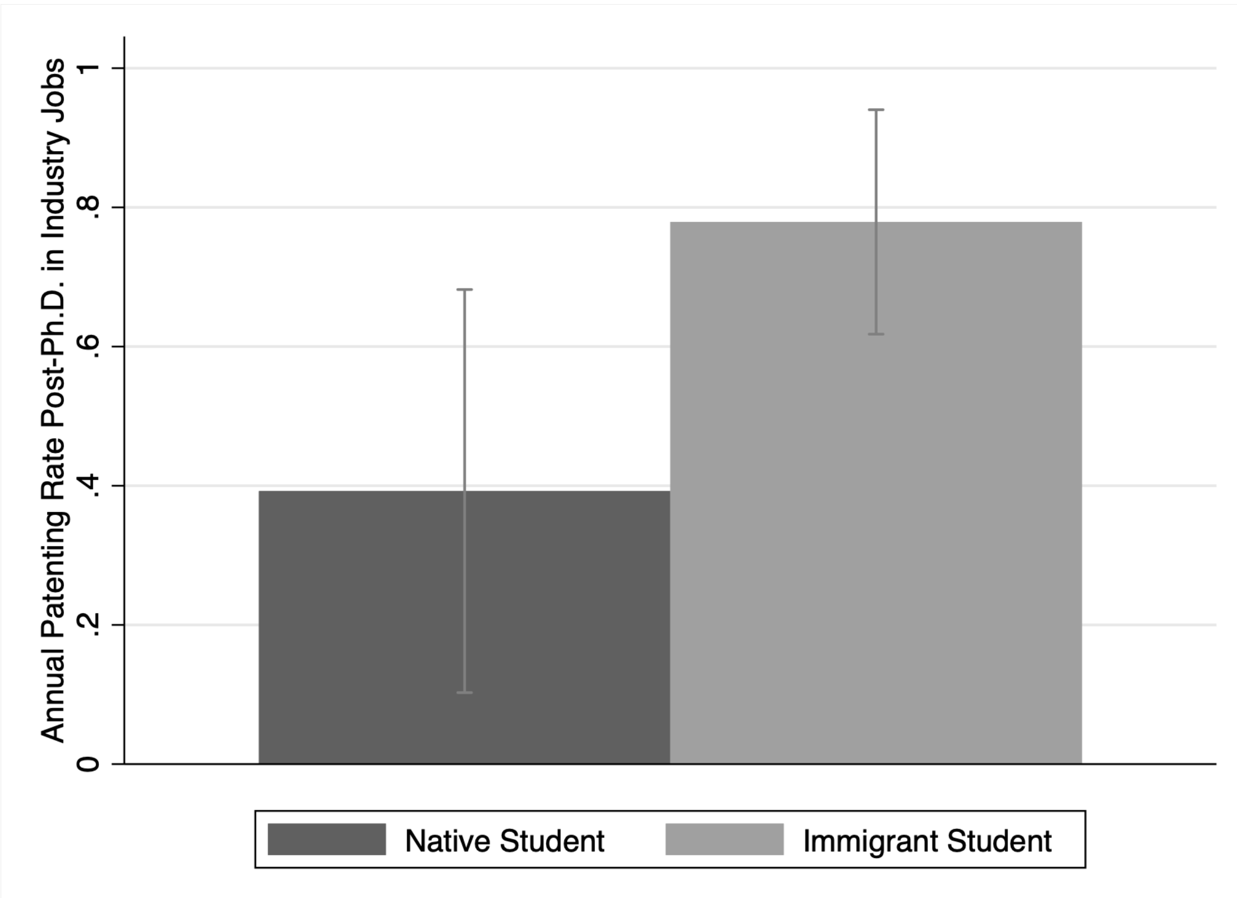
Notes: Students were asked: How did your Ph.D. advisor influence your choice of post-Ph.D. job? (Select all that apply). They selected from: Encouraged pursuing academic roles; Provided academic networking opportunities (e.g., conferences, introductions to academic coauthors and researchers); Guided my research towards more theoretical questions; Encouraged pursuing industry roles; Guided my research towards industry applications; Provided industry networking opportunities (e.g., introductions to industry professionals, alumni, or coauthors); Facilitated industry internships. For each option, we plot the average share of respondents who selected it (coded as 1 if selected, 0 otherwise), with averages and confidence intervals shown separately for each group of survey respondents. Native are those completing undergraduate education in the U.S.. Asian LMIC students are those completing undergraduate education in Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka, or Vietnam. Other immigrants are all other non-U.S. undergraduate locations.

Figure A5: Job Applications and Offers



Notes: We asked graduates: For the next set of questions, please consider only your first job: What types of positions did you apply for? (Select all that apply). And separately "In which sectors did you receive job offers? (Select all that apply). They selected from: Industry (e.g., tech companies), academia (e.g., postdocs, faculty), Other (please specify. For each option, we plot the average share of respondents who selected it (coded as 1 if selected, 0 otherwise), with averages and confidence intervals shown separately for each group of survey respondents. Native are those completing undergraduate education in the U.S.. Asian LMIC students are those completing undergraduate education in Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka, or Vietnam. Other immigrants are all other non-U.S. undergraduate locations.

Figure A6: Post-Ph.D. Patenting Rate in Industry



Notes: We plot the average annual patent counts for up to six years post-Ph.D. across sample immigrant and natives who take their first job in industry.

Table A1: Undergraduate Country for Study Sample AI Students

Undergraduate Country	Nb Sample Students	% of Student Sample
Argentina	2	0.11
Australia	10	0.57
Austria	2	0.11
Bangladesh	5	0.28
Brazil	8	0.46
Bulgaria	1	0.06
Canada	37	2.11
Chile	2	0.11
China	360	20.49
Colombia	4	0.23
Croatia	1	0.06
Denmark	1	0.06
Egypt	9	0.51
Finland	2	0.11
France	5	0.28
Georgia	1	0.06
Germany	16	0.91
Greece	5	0.28
Iceland	1	0.06
India	143	8.14
Iran	55	3.13
Ireland	2	0.11
Israel	10	0.57
Italy	7	0.40
Japan	4	0.23
Kuwait	1	0.06
Latvia	1	0.06
Lebanon	4	0.23
Mexico	6	0.34
New Zealand	3	0.17
Pakistan	3	0.17
Peru	1	0.06
Poland	2	0.11
Puerto Rico	2	0.11
Russian Federation	9	0.51
Saudi Arabia	2	0.11
Serbia	1	0.06
Singapore	11	0.63
Slovenia	2	0.11
South Korea	50	2.85
Spain	2	0.11
Sri Lanka	5	0.28
Sweden	2	0.11
Switzerland	2	0.11
Taiwan	44	2.50
Thailand	4	0.23
The Netherlands	3	0.17
United Kingdom	15	0.85
United States	839	47.75
Uruguay	1	0.06
Venezuela	1	0.06
Vietnam	2	0.11

Notes: This sample consists of 1,757 artificial intelligence U.S. PhD students. Despite being a territory of the United States, Puerto Rico is considered separate for the purposes of this study due to cultural distance.

Table A2: Undergraduate Country for Study Sample Advisors of AI Students

Undergraduate Country	Nb Advisors	% of Advisor Sample
Algeria	1	0.07
Argentina	4	0.28
Armenia	1	0.07
Australia	13	0.92
Austria	3	0.21
Bangladesh	1	0.07
Belgium	8	0.57
Brazil	3	0.21
Bulgaria	2	0.14
Canada	36	2.49
Chile	3	0.21
China	95	6.75
Colombia	1	0.07
Denmark	2	0.14
Dominican Republic	1	0.07
Egypt	3	0.21
Finland	2	0.14
France	18	1.28
Germany	25	1.78
Greece	18	1.28
Hungary	2	0.14
India	91	6.46
Iran	20	1.42
Iraq	1	0.07
Ireland	4	0.28
Israel	32	2.27
Italy	17	1.14
Japan	7	0.50
Jordan	1	0.07
Kuwait	1	0.07
Lebanon	3	0.21
Mexico	3	0.21
New Zealand	5	0.36
Norway	1	0.07
Poland	3	0.21
Portugal	4	0.28
Romania	8	0.57
Russian Federation	2	0.14
Serbia	3	0.21
Slovenia	2	0.14
Slovakia	1	0.07
South Africa	1	0.07
South Korea	9	0.64
Spain	8	0.57
Sweden	2	0.14
Switzerland	5	0.36
Taiwan	15	1.07
Thailand	1	0.07
Turkey	9	0.64
The Netherlands	6	0.43
United Kingdom	25	2.13
United States	770	54.97
Uruguay	1	0.07
Unknown	100	6.96

Notes: This sample consists of 1,408 advisors of artificial intelligence U.S. PhD students.

Table A3: Descriptives - native and immigrant students

	Native Student (N = 839) (1)		Immigrant Student (N = 918) (2)		(2)-(1)
	mean	std. dev.	mean	std. dev.	mean (std. dev.)
Ph.D. graduation year	2016	1.41	2017	1.38	0.013 (0.066)
Top 10 Ph.D. institution	0.64	0.48	0.52	0.50	-0.12*** (0.023)
Pre-Ph.D. graduation number of publications	4.37	7.69	7.21	9.61	2.84*** (0.42)
Any immigrant advisor	0.33	0.47	0.53	0.50	0.20*** (0.023)
Maximum advisor industry collaborative publications	4.97	8.04	7.67	10.64	2.70*** (0.45)
Work in U.S. post Ph.D. graduation	0.94	0.23	0.92	0.29	-0.027** (0.012)
First job industry	0.51	0.50	0.65	0.48	0.14*** (0.023)
First job top AI industry employer	0.26	0.44	0.45	0.50	0.19*** (0.022)
First job academia	0.43	0.50	0.33	0.47	-0.10*** (0.023)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: [a] This sample consists of 1,757 artificial intelligence U.S. PhD students. Native are those completing undergraduate education in the U.S.. Immigrants are those with any non-U.S. undergraduate locations. Pre-PhD graduation publications are those authored by the student during the PhD time. Maximum advisor industry collaborative publications are the maximum of all advisors (if the student has more than one advisor) publications coauthored with industry affiliated researchers, measured in the five years prior to the PhD start year. Top AI employers are 22 U.S. firms that are top valued on the stock market, or rated as employers in 2018 by Forbes and Business Insider.

Table A4: Immigrant Students and Diasporic Advisors, excluding non-S&E Students

	Advisor with Non-U.S. Undergraduate		Advisor with LMIC Asian Country Undergraduate		Advisor With Same Undergraduate Country, Just Immigrant Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant student	0.1557***	0.1398***				
	(0.028)	(0.028)				
Asian LMIC student			0.1182***	0.1104***	0.0844***	0.0905***
			(0.025)	(0.025)	(0.028)	(0.028)
Other immigrant student			0.0376	0.0263		
			(0.023)	(0.023)		
Total Observations	1555	1555	1555	1555	843	843
Mean of Dep. Variable	0.4476	0.4476	0.1659	0.1659	0.1530	0.1530
Graduation Year FE	X	X	X	X	X	X
PhD Department FE	X	X	X	X	X	X
PhD Institution FE	X	X	X	X	X	X
Pre-PhD Publications		X		X		X
Pre-PhD Industry Job		X		X		X
Advisor Industry Publications		X		X		X
Advisor H-index		X		X		X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: [a] Estimates stem from OLS regression in which dependent variables are dummy outcomes. Immigrant student are those with non-U.S. undergraduates. Asian LMIC student include those with undergraduate degrees from Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka, or Vietnam. Other immigrant students are all other non-U.S. undergraduate locations. Columns 1-2 report the likelihood of having at least one non-U.S. educated advisor. Columns 3-4 report the likelihood of having at least one advisor educated in an Asian LMIC country. Columns 5-6 report the likelihood of sharing the same undergraduate country as an advisor (restricted to the immigrant student sample). Odd-numbered columns include institution, department, and graduation year fixed effects, while even-numbered columns add student and advisor controls. The sample excludes students who are in non S&E departments. [b] Heteroskedastic robust standard errors clustered at the level of the advisor are given in parentheses.

Table A5: Advisor Name Nationality

	Advisor with Asian Name Ethnicity		Advisor With Same Name Ethnicity, Just Immigrant Sample	
	(1)	(2)	(3)	(4)
Asian LMIC student	0.1800***	0.1638***	0.0773***	0.0770***
	(0.028)	(0.027)	(0.029)	(0.029)
Other immigrant student	0.0555**	0.0416*		
	(0.025)	(0.024)		
Total Observations	1757	1757	918	918
Mean of Dep. Variable	0.2470	0.2470	0.2048	0.2048
Graduation Year FE	X	X	X	X
PhD Department FE	X	X	X	X
PhD Institution FE	X	X	X	X
Pre-PhD Publications		X		X
Pre-PhD Industry Job		X		X
Advisor Industry Publications		X		X
Advisor H-index		X		X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: [a] Estimates stem from OLS regression in which dependent variables are dummy outcomes. Asian LMIC student include those with undergraduate degrees from Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka, or Vietnam. Other immigrant students are all other non-U.S. undergraduate locations. Columns 1-2 report the likelihood of having at least one non-U.S. educated advisor. Columns 1-2 report the likelihood of having at least one advisor with an Asian name ethnicity. Columns 3-4 report the likelihood of sharing the same name ethnicity as an advisor (restricted to the immigrant student sample). Odd-numbered columns include institution, department, and graduation year fixed effects, while even-numbered columns add student and advisor controls. [b] Heteroskedastic robust standard errors, clustered at the level of the PhD advisor, are given in parentheses.

Table A6: Robustness of Advisor Matching

	Advisor with LMIC Asian Country Undergraduate		Advisor with LMIC Asian, not Home, Undergraduate	Advisor with LMIC Asian Country Undergraduate Excl. Chinese	Advisor with LMIC Asian Country Undergraduate Excl. Indian
	(1)	(2)	(3)	(4)	(5)
Asian LMIC student	0.1231***	0.1227***	-0.0470***	0.0969***	0.1237***
	(0.023)	(0.023)	(0.018)	(0.033)	(0.028)
Other immigrant student	0.0262	0.0266	0.0424**	0.0254	0.0268
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Asian faculty at university		-0.0002			
		(0.000)			
Total Observations	1757	1757	1757	1396	1614
Mean of Dep. Variable	0.1537	0.1537	0.0922	0.4470	0.4077
Graduation Year FE	X	X	X	X	X
PhD Department FE	X	X	X	X	X
PhD Institution FE	X	X	X	X	X
Pre-PhD Publications	X	X	X	X	X
Pre-PhD Industry Job	X	X	X	X	X
Advisor Industry Publications	X	X	X	X	X
Advisor H-index	X	X	X	X	X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: [a] Estimates stem from OLS regression in which dependent variables are dummy outcomes. Asian LMIC student include those with undergraduate degrees from Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka, or Vietnam. Other immigrant students are all other non-U.S. undergraduate locations. Column 1 reports the baseline likelihood of having at least one advisor educated in an Asian LMIC country. Column 2 adds a control from the number of Asian faculty at the student's university in the PhD start year. Column 3 reports the likelihood report the likelihood of having at least one advisor educated in an Asian LMIC country other than the student's own undergraduate country. Column 4 excludes students from China; Column 5 excludes students from India. All columns include institution, department, and graduation year fixed effects, as well as student and advisor controls (pre-PhD publications, pre-PhD industry job, advisor industry publications, and advisor h-index). [b] Heteroskedastic robust standard errors, clustered at the level of the PhD advisor, are given in parentheses.

Table A7: Alternative Measures of Industry Orientation

	Any Industry Coauthored Publications During PhD		Mean Industry Orientation of Publications During PhD	
	(1)	(2)	(3)	(4)
Immigrant student	0.0726***		0.0074**	
	(0.017)		(0.003)	
Asian LMIC student		0.0870***		0.0111***
		(0.022)		(0.004)
Other immigrant student		0.0560***		0.0019
		(0.020)		(0.004)
Total Observations	1757	1757	856	856
Mean of Dep. Variable	0.1969	0.1969	0.1609	0.1609
Year FE	X	X	X	X
Department FE	X	X	X	X
Institution FE	X	X	X	X
Pre-PhD Industry Job	X	X	X	X
Pre-PhD Publications	X	X	X	X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: [a] Estimates stem from OLS regression in which dependent variables are dummy outcomes. Asian LMIC student include those with undergraduate degrees from Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka, or Vietnam. Other immigrant students are all other non-U.S. undergraduate locations. Columns 1-2 report the likelihood of the student authoring any industry coauthored publication during their PhD. Columns 3-4 report the average industry orientation of publications authored during the PhD (restricted to the sample of students with at least one publication during PhD).
[b] Heteroskedastic robust standard errors, clustered at the level of the PhD advisor, are given in parentheses.

Table A8: Advisor Industry Orientation

	Advisor Industry Collaborative Publications		Advisor Unique Industry Collaborations		Advisor Top Industry Collaborative Publications		Advisor Industry Funders	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigrant student	0.1094**		0.1108*		0.1740***		0.0039	
	(0.049)		(0.058)		(0.046)		(0.003)	
Asian LMIC student		0.1779***		0.1975***		0.2709***		0.0041
		(0.061)		(0.072)		(0.058)		(0.004)
Other immigrant student		0.0309		0.0113		0.0627		0.0037
		(0.059)		(0.067)		(0.055)		(0.005)
Total Observations	1757	1757	1757	1757	1757	1757	1757	1757
Mean of Dep. Variable	6.3808	6.3808	6.6522	6.6522	1.7245	1.7245	0.0057	0.0057
Year FE	X	X	X	X	X	X	X	X
Department FE	X	X	X	X	X	X	X	X
Institution FE	X	X	X	X	X	X	X	X
Pre-PhD Industry Job	X	X	X	X	X	X	X	X
Pre-PhD Publications	X	X	X	X	X	X	X	X
Advisor Publications	X	X	X	X	X	X	X	X
Advisor H-Index	X	X	X	X	X	X	X	X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: [a] Estimates stem from OLS regression in which dependent variables are dummy outcomes. Asian LMIC student include those with undergraduate degrees from Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka, or Vietnam. Other immigrant students are all other non-U.S. undergraduate locations. Columns 1-2 report the (maximum) volume of advisor industry collaborative publications in the five years prior to the students' PhD start year. Columns 3-4 report the (maximum) volume of advisor unique industry collaborators in the five years prior to the students' PhD start year. Columns 5-6 report the (maximum) volume of advisor top industry collaborators in the five years prior to the students' PhD start year. Columns 7-8 report the (maximum) volume of advisor unique industry funders of publications in the five years prior to the students' PhD start year.
[b] Advisor industry funders is the count of unique industry funding sources on the advisor's publications in the five years prior to the student's PhD start year. Industry funders were identified from the publication-level funder variable in OpenAlex. We classified funders as industry or non-industry in two steps: first using an automated screen to remove obvious non-industry funders (government agencies, nonprofits, universities), then manually verifying the remaining cases. The mean is very low, likely reflecting incomplete coverage of funding metadata in OpenAlex, so these results should be interpreted with caution.
[c] Heteroskedastic robust standard errors, clustered at the level of the PhD advisor, are given in parentheses.

Table A9: Career Outcomes - U.S. stayers only

	Industry Job Post PhD			Top Industry Job Post PhD		
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant student	0.1212***			0.1545***		
	(0.027)			(0.023)		
Asian LMIC student		0.1508***	0.1173***		0.1875***	0.0850***
		(0.030)	(0.030)		(0.028)	(0.021)
Other immigrant student		0.0694**	0.0422		0.1144***	0.0600***
		(0.032)	(0.032)		(0.029)	(0.021)
Industry internship			0.2081***			
			(0.027)			
Top industry internship						0.7437***
						(0.019)
Total Observations	1630	1630	1630	1630	1630	1630
Mean of Dep. Variable	0.6012	0.6012	0.6012	0.3669	0.3669	0.3669
Year FE	X	X	X	X	X	X
Department FE	X	X	X	X	X	X
Institution FE	X	X	X	X	X	X
Pre-PhD Industry Job	X	X	X	X	X	X
Pre-PhD Publications	X	X	X	X	X	X
During-PhD Publications	X	X	X	X	X	X
Advisor Industry Publications	X	X	X	X	X	X
Advisor H-index	X	X	X	X	X	X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: [a] Only U.S. stayers in the first job post PhD are retained in the sample. Estimates stem from OLS regression in which dependent variables are dummy outcomes. Immigrant student are those with non-U.S. undergraduates. Asian LMIC student include those with undergraduate degrees from Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka, or Vietnam. Other immigrant students are all other non-U.S. undergraduate locations. Columns 1-3 report the likelihood of having an industry job as first job post-PhD. Columns 4-6 report the likelihood of having a top AI job as first job post-PhD. Column 3 adds an indicator for whether the student undertook an industry internship during the PhD. Column 6 adds an indicator for whether the student undertook a top industry internship during the PhD. Top AI employers are 22 U.S. firms that are top valued on the stock market, or rated as employers in 2018 by Forbes and Business Insider. [b] Heteroskedastic robust standard errors, clustered at the level of the PhD advisor, are given in parentheses.

Table A10: Career Outcomes - post 2016 graduation

	Industry Job Post PhD			Top Industry Job Post PhD		
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant student	0.0947***			0.1473***		
	(0.036)			(0.032)		
Asian LMIC student		0.1477***	0.0920**		0.2069***	0.0731***
		(0.040)	(0.040)		(0.037)	(0.027)
Other immigrant student		0.0141	-0.0200		0.0685*	0.0063
		(0.046)	(0.045)		(0.041)	(0.028)
Industry internship			0.2573***			
			(0.037)			
Top industry internship						0.7597***
						(0.027)
Total Observations	871	871	871	871	871	871
Mean of Dep. Variable	0.6096	0.6096	0.6096	0.3823	0.3823	0.3823
Year FE	X	X	X	X	X	X
Department FE	X	X	X	X	X	X
Institution FE	X	X	X	X	X	X
Pre-PhD Industry Job	X	X	X	X	X	X
Pre-PhD Publications	X	X	X	X	X	X
During-PhD Publications	X	X	X	X	X	X
Advisor Industry Publications	X	X	X	X	X	X
Advisor H-index	X	X	X	X	X	X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: [a] Only Ph.D.s graduating post-2016 are retained in the sample. Estimates stem from OLS regression in which dependent variables are dummy outcomes. Immigrant student are those with non-U.S. undergraduates. Asian LMIC student include those with undergraduate degrees from Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka, or Vietnam. Other immigrant students are all other non-U.S. undergraduate locations. Columns 1-2 report the likelihood of having at least one non-U.S. educated advisor. Columns 3-4 report the likelihood of having at least one advisor educated in an Asian LMIC country. Columns 1-4 report the likelihood of taking an industry job in the first job post-PhD. Columns 5-8 report the likelihood of taking a top industry job as the first job post PhD. Top AI employers are 22 U.S. firms that are top valued on the stock market, or rated as employers in 2018 by Forbes and Business Insider.
[b] Heteroskedastic robust standard errors, clustered at the level of the PhD advisor, are given in parentheses.

Table A11: Immigrant Top AI Job Heterogeneity by Ph.D. features

	Top 10 PhD Institution	Not Top 10 PhD Institution	Computer Science PhD Department	Not Computer Science PhD Department
	(1)	(2)	(3)	(4)
Asian LMIC student	0.0828***	0.0785***	0.0825**	0.0925***
	(0.028)	(0.030)	(0.041)	(0.023)
Other immigrant student	0.0406*	0.0371	0.0646	0.0361*
	(0.024)	(0.032)	(0.048)	(0.020)
Top industry internship	0.7766***	0.7215***	0.6239***	0.8188***
	(0.023)	(0.033)	(0.040)	(0.018)
Total Observations	1013	744	406	1351
Mean of Dep. Variable	0.3791	0.3333	0.6502	0.2724
Year FE	X	X	X	X
Department FE	X	X	X	X
Institution FE	X	X	X	X
Pre-PhD Industry Job	X	X	X	X
Pre-PhD Publications	X	X	X	X
During-PhD Publications	X	X	X	X
Advisor Industry Publications	X	X	X	X
Advisor H-index	X	X	X	X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: [a] Estimates stem from OLS regression in which dependent variables are dummy outcomes. Asian LMIC student include those with undergraduate degrees from Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka, or Vietnam. Other immigrant students are all other non-U.S. undergraduate locations. All columns report the likelihood of having an top AI industry job as the first job post PhD. Top AI employers are 22 U.S. firms that are top valued on the stock market, or rated as employers in 2018 by Forbes and Business Insider. Column 1 includes just students at top 10 PhD institutions. Column 2 includes students in top 11-20 PhD institutions. Column 3 includes just students in computer science departments for their PhD. Column 4 excludes computer science department PhDs.
[b] Heteroskedastic robust standard errors, clustered at the level of the PhD advisor, are given in parentheses.

Appendix B

Advisor–Student Matching: Advisor-Side and Dyad-Level Evidence

This appendix provides supplementary evidence on conational advisor–student matching from the advisor perspective and using a dyad-level design.

We first examine matching patterns from the advisor side. Appendix Table B1 shows that immigrant faculty are more likely than U.S.-educated faculty to supervise immigrant PhD students. However, this relationship is highly heterogeneous by advisors' country of origin. The elevated propensity to advise immigrant students is concentrated among Asian LMIC faculty. These advisors are more than 23 percentage points more likely to supervise at least one Asian LMIC student and over 30 percentage points more likely to supervise at least one student from their own undergraduate country. By contrast, immigrant faculty from other regions do not display a statistically significant tendency to advise immigrant students. These results mirror the student-side evidence and underscore the central role of diaspora faculty in shaping entry into the doctoral pipeline.

To further assess whether these patterns reflect systematic matching rather than compositional differences or spurious correlations, we employ a dyad-level approach in Appendix Table B2. In this design, each student is paired with every potential advisor within the same field, as defined by department names, and, in extended specifications, within the same field and institution. This construction allows us to compare realized advisor–student pairings against the full set of feasible matches available to each student.

Because this approach expands the data to include all possible student–advisor dyads, groups with very different underlying sizes generate different numbers of potential matches. As a result, coefficient magnitudes across subgroups should be interpreted with caution. Nonetheless, the results consistently show that realized matches are systematically skewed toward conational pairings. This pattern persists after controlling for shared commercial orientation and similarity in academic productivity between students and advisors (Appendix Table B2, columns 2, 4, and 8).

Importantly, the dyad-level evidence indicates that matching is driven by shared country of origin rather than by general immigrant status. Student–advisor pairs that share the same undergraduate country are significantly more likely to form, with the effect especially pronounced for immigrant students (columns 3, 4, 7, and 8). These findings confirm that the conational matching documented in the main analysis is not an artifact of advisor availability or student sorting across fields, but reflects a systematic preference for shared national origin in advisor–advisee relationships.

Advisor Networks, Institutional Context, and Internship Participation

This appendix provides additional evidence on how the role of advisor networks in facilitating industry internships varies across institutional and disciplinary contexts. The analysis extends the main results by examining heterogeneity in the relationship between advisors' industry ties and students' internship participation. Appendix Table B3 reports estimates of internship regressions stratified by institutional rank and department. In top-ten PhD institutions (Column 1), advisors' industry coauthorships are not significantly associated with students' likelihood of undertaking an industry internship, and the interaction between advisor industry ties and Asian LMIC status is positive but only marginally significant. By contrast, in non–top-ten institutions (Column 2), the interaction between advisor industry collaborations and Asian LMIC status is larger and statistically significant: Asian LMIC students advised by faculty with industry co-publications are approximately 5.4 percentage points more likely to undertake an internship, while the main association between advisor industry ties and internships remains close to zero.

A similar pattern emerges when comparing computer science and non–computer science departments. In computer science departments (Column 3), neither advisor industry collaborations nor their interaction with Asian LMIC status are meaningfully related to internship participation. In departments outside computer science (Column 4), however, the interaction between advisor industry publications and Asian LMIC status is again positive and statistically significant (0.0499). These results indicate that advisor networks are more consequential for internship access in settings where formalized university–industry pipelines are less developed.

Together, these patterns are consistent with a substitution mechanism between institutionalized and advisor-mediated pathways into industry. In elite computer science departments and top-ranked institutions, where students often have access to established recruiting pipelines, formal partnerships, and routine internship placements, advisor-specific industry ties play a more limited role. By contrast, in less centralized institutional environments, advisor networks and personal collaborations appear to serve as an important substitute, particularly for Asian LMIC students.

Qualitative interview evidence aligns with this interpretation. Students in mid-tier or non–computer science programs frequently described relying on advisors' contacts to identify and secure internship opportunities, whereas students in elite computer science departments emphasized the availability of structured departmental pipelines. One interviewee noted that at a top-ranked program, "almost everyone had internships because the department had ongoing partnerships with leading companies," while the same interviewee noted that industry internships were relatively uncommon in a mid-tier program without such institutionalized links.

Table B1: Advisor Trends

	Probability of Immigrant Student		Probability of Asian, LMIC Student		Probability of Same Country Student, Just Immigrant Advisor Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant faculty	0.1333***	0.1310***				
	(0.026)	(0.026)				
Asian LMIC faculty			0.2277***	0.2347***	0.3023***	0.3132***
			(0.038)	(0.039)	(0.038)	(0.039)
Other immigrant faculty			-0.0164	-0.0159		
			(0.025)	(0.026)		
Total Observations	1408	1408	1408	1408	535	535
Mean of Dep. Variable	0.5105	0.5105	0.5105	0.5105	0.6184	0.6184
Year FE	X	X	X	X	X	X
Department FE	X	X	X	X	X	X
Institution FE	X	X	X	X	X	X
Industry Publications		X		X		X
H-index		X		X		X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: [a] Data is at the level of the faculty in the sample. Estimates stem from OLS regression in which dependent variables are dummy outcomes. Immigrant faculty are those with non-U.S. undergraduates. Asian LMIC faculty include those with undergraduate degrees from Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka, or Vietnam. Other immigrant faculty are all other non-U.S. undergraduate locations. We include a dummy variable in all specifications for whether the advisor has more than one advisee in the sample. Columns 1-2 report the likelihood of having at least one student with a non-U.S. undergraduate education. Columns 3-4 report the likelihood of having at least one student with an Asian LMIC undergraduate education. Columns 5-6 report the likelihood of sharing the same undergraduate country as a student (restricted to the immigrant advisor sample).
[b] Heteroskedastic robust standard errors, clustered at the level of the PhD advisor, are given in parentheses.

Table B2: Determinants of Student Advisor Pairing

	Within Department				Within Department and University			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Student and advisor share undergraduate country	0.0013***	0.0013***	0.0009***	0.0009***	0.0141***	0.0142***	0.0079***	0.0081***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.003)	(0.003)
Student and advisor share commercial orientation		0.0002		0.0002		0.0029		0.0023
		(0.000)		(0.000)		(0.003)		(0.003)
Student and advisor share academic productivity		0.0004**		0.0003*		0.0037		0.0034
		(0.000)		(0.000)		(0.003)		(0.003)
Student and advisor share undergraduate country × Immigrant student			0.0049***	0.0048***			0.0582***	0.0576***
			(0.001)	(0.001)			(0.009)	(0.009)
Immigrant student			0.0002	0.0002			-0.0003	-0.0002
			(0.000)	(0.000)			(0.002)	(0.002)
Total Observations	651840	651840	651840	651840	46320	46320	46320	46320
Mean of Dep. Variable	0.0029	0.0029	0.0029	0.0029	0.0403	0.0403	0.0403	0.0403
Year FE	X	X	X	X	X	X	X	X
Department FE	X	X	X	X	X	X	X	X
Institution FE	X	X	X	X	X	X	X	X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: [a] Data is at the level of the student, advisor pair. Estimates stem from OLS regression in which dependent variables are dummy outcomes that take the value of 1 if a student, advisor pair is realized. In Columns 1-4 the student, advisor pairs are limited to just those within the same broad department type (such as engineering, or economics); in columns 5-8 the student, advisor pairs are limited to just those within the same institution and broad department type (such as engineering at MIT). Shared undergraduate country takes the value of 1 if a student and advisor both have an undergraduate degree from the same country. Shared commercial orientation takes the value of 1 if student has an industry employer pre-Ph.D. and if advisor has above median industry collaborations; shared academic productivity takes the value of 1 if student has any pre-Ph.D. publications and advisor has above median publications. Immigrant student are those with non-U.S. undergraduates.
[b] Heteroskedastic robust standard errors, clustered at the level of the PhD advisor, are given in parentheses.

Table B3: Heterogeneity of Industry Internships

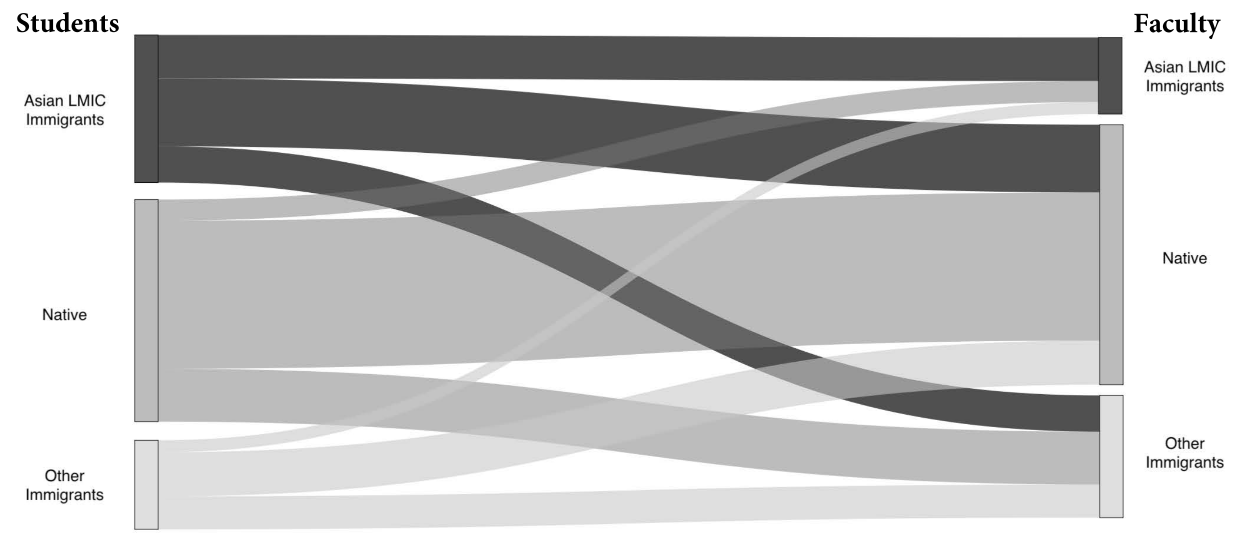
	Top 10 PhD Institution	Not Top 10 PhD Institution	Computer Science PhD Department	Not Computer Science PhD Department
	(1)	(2)	(3)	(4)
Asian LMIC student	0.0559	0.0509	0.1397	0.0431
	(0.058)	(0.053)	(0.125)	(0.038)
Other immigrant student	0.0746	0.0208	0.0241	0.0456
	(0.053)	(0.042)	(0.137)	(0.033)
Advisor Industry Pubs	0.0127	-0.0126	0.0121	0.0031
	(0.015)	(0.015)	(0.035)	(0.011)
Advisor Industry Pubs × Asian LMIC student	0.0435*	0.0540**	-0.0009	0.0499***
	(0.025)	(0.024)	(0.049)	(0.018)
Advisor Industry Pubs × Other immigrant student	-0.0002	0.0403	0.0365	0.0083
	(0.025)	(0.025)	(0.057)	(0.018)
Total Observations	1013	744	406	1351
Mean of Dep. Variable	0.2705	0.2177	0.5148	0.1680
Year FE	X	X	X	X
Department FE	X	X	X	X
Institution FE	X	X	X	X
Pre-PhD Industry Job	X	X	X	X
Pre-PhD Publications	X	X	X	X
Advisor H-index	X	X	X	X

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

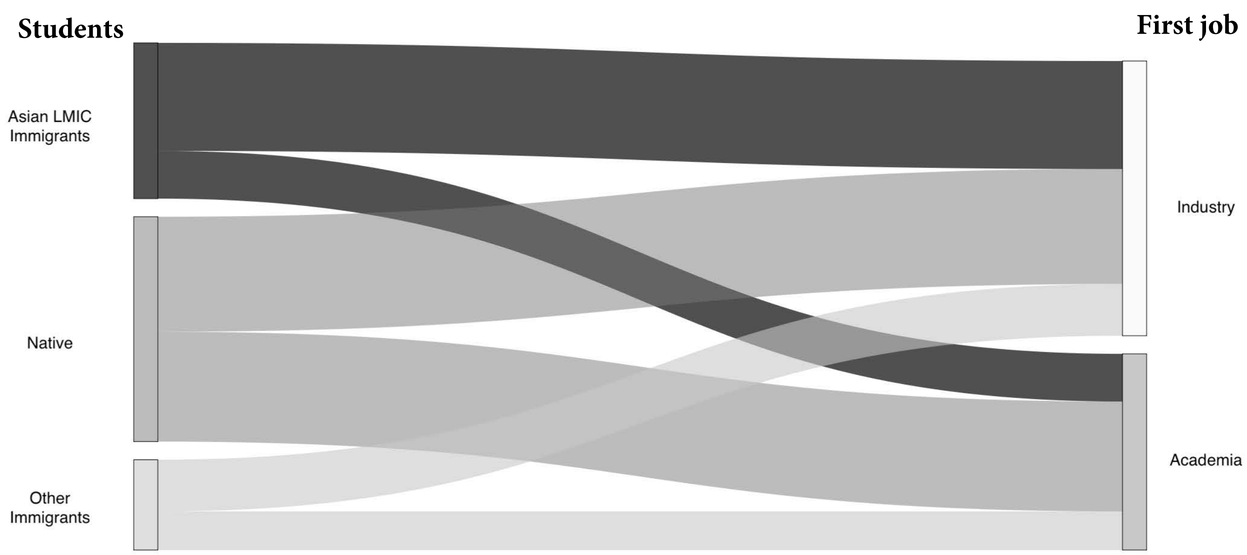
Notes: [a] Estimates stem from OLS regression in which dependent variables are dummy outcomes. Asian LMIC student include those with undergraduate degrees from Bangladesh, China, India, Cambodia, Malaysia, Pakistan, the Philippines, Thailand, Sri Lanka, or Vietnam. Other immigrant students are all other non-U.S. undergraduate locations. All columns report the likelihood of having an industry internship during the PhD. Column 1 includes just students at top 10 PhD institutions. Column 2 includes students in top 11-20 PhD institutions. Column 3 includes just students in computer science departments for their PhD. Column 4 excludes computer science department PhDs. [b] Heteroskedastic robust standard errors, clustered at the level of the PhD advisor, are given in parentheses.

Appendix C

Figure C1: Student–advisor and student–industry flows.



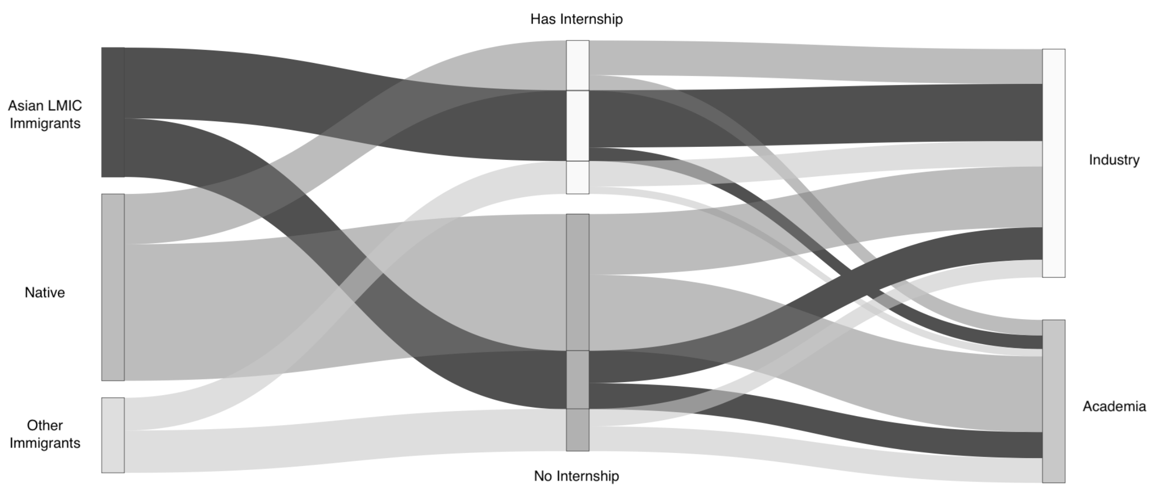
(a) Flows from students' undergraduate countries to advisors' undergraduate countries.



(b) Flows from students' undergraduate countries to post-PhD employment sectors.

Notes: Sankey diagrams showing flows between student origins, advisor origins (Panel a), and employment sectors (Panel b). Line width represents the volume of students. Students are grouped by undergraduate country: Native (U.S.), Asian LMIC (Low and Middle-Income Countries including China, India, and others), and Other Immigrants. Faculty and employment sectors are similarly grouped. Sample includes 1,757 AI PhD graduates from top U.S. programs, 2014-2018.

Figure C2: Asian LMIC Talent Industry Inflow via Internship



Notes: Sankey diagram showing the relationship between internship participation during the PhD and first job placement for sample students grouped by origin (Native, Asian LMIC, Other Immigrants). Left side shows students split by whether they completed an internship during their PhD. Right side shows first job sector (Industry or Academia). Line width represents volume of students. Asian LMIC students show the highest rates of internship participation and the strongest flows from internships into industry positions, particularly in elite AI firms.

Appendix D

Appendix D.1 Survey Response Rate by Group

Table D1: Survey Response Rate

Research Field	% of PhD Student Sample Responded	% of Advisor Sample Responded
Overall	14%	10%
Native	17%	12%
Immigrant	9%	9%
Biology	18%	3%
Chemistry	14%	10%
Computer Science	14%	9%
Engineering	10%	7%
Environmental Science	50%	0%
Geology	22%	18%
Materials Science	0%	0%
Mathematics	19%	14%
Medicine	21%	11%
Physics	11%	8%
nonSE Subjects	19%	21%

Note: "nonSE" stands for "non-science-or-engineering" fields

Appendix D.2 Advisor Survey

1. Please rank the following factors based on how important they are in your decision-making process for selecting PhD students. *Please drag each option up or down to reflect their order of importance, with the top (1) = most important and the bottom (5) = least important.*

_________ Shared backgrounds or affiliations (e.g., same university, home country, cultural familiarity) (1)

_________ Academic performance (e.g., grades, test scores) (2)

_________ Alignment of research interests (3)

_________ Previous exposure to the candidate through, e.g., conferences or meetings (4)

_________ Connections or recommendations through my network (5)

. . . .

If any important factors were missed above, please write them here.

____

2. Think about your most recent student(s) who went into industry *(e.g., start-ups, tech companies). What are the top (up to) three factors that you think contributed to that outcome:*

- ☐ I have many coauthors in industry who I connect my students with (1)
- ☐ My department has strong connections with industry (e.g., large alumni network, industry funding, partnerships) (2)
- ☐ I often facilitate industry internships for my students. (3)
- ☐ The research we conduct in my lab is more applied in nature. (4)
- ☐ I tend to select students who are interested in industry positions even before they arrive. (5)
- ☐ I think industry jobs offer better opportunities, so I encourage my students to go into industry. (6)
- ☐ They were unable to get an academic job. (7)
- ☐ None of my students have gone into industry (8)

3. Think about your most recent student(s) who went into academia (e.g., postdocs, tenure track positions). *What are the top (up to) three factors that you think contributed to that outcome:*

- ☐ I have a strong academic coauthorship network. (1)
- ☐ Our department has a large alumni network in academia. (2)
- ☐ Our department is well-regarded in academia. (3)
- ☐ The research we conduct in my lab/department is more theoretical or basic in nature. (4)
- ☐ I tend to select students who express a strong interest in academic careers during the application process. (5)
- ☐ I encourage my students to pursue academic jobs because I believe they offer the best opportunities for research. (6)
- ☐ They were unable to get an industry job. (7)
- ☐ None of my students have gone into academia (8)

4. If you are able to provide some context regarding why your students went into industry or academia, beyond or as a complement to the multiple choice answers above, please describe here.

5. Approximately how many students have you advised in the past five years?

☐ Fewer than five (1)

☐ 6-10 (2)

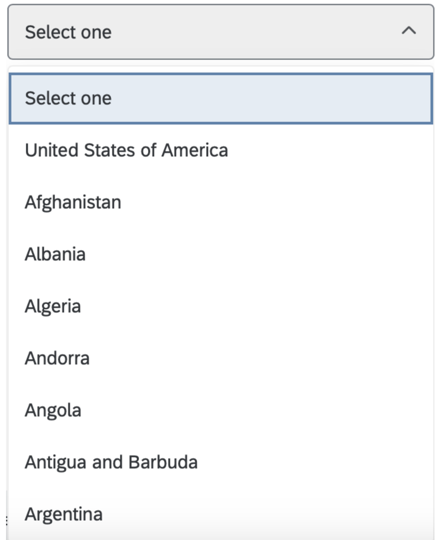
☐ 11+ (3)

6. And approximately what proportion of those students have gone into industry?

50

0 100

7. In what country did you spend most of your childhood (before age 18)? *(If you lived in multiple countries, please select the one where you spent the majority of your time.)*



(display next question if "United States of America" is not selected in question 7)

Do you find that you often work with PhD students from your home country?

☐ Yes (1)

☐ No (2)

(display next TWO question if "Yes" is not selected in last question)

Please explain why by selecting all applicable reasons below.

☐ I can better assess their academic and cultural background (1)

☐ We have common contacts or a shared network (2)

☐ I can communicate effectively with them (e.g., language, cultural nuances) (3)

☐ They actively seek opportunities to work with me (4)

If there are additional important reasons or context, please explain briefly.

____

8. We are seeking individuals to interview over Zoom regarding their experiences as a PhD advisor. If you would be interested in talking with us about your experiences, please enter your email below. Your interview responses will be kept confidential.

Appendix D.3 Student Survey

1. What was your primary motivation for pursuing a PhD? *Please drag each option up or down to reflect their order of importance, with the top (1) = most important and the bottom (4) = least important.*

________ Passion for research (1)

________ Desire for a career in academia (2)

________ Desire for a career in industry (e.g., start-ups, tech companies) (3)

________ Encouragement from a mentor/advisor (4)

. . . .

If any important factors were missed above, please write them here.

____

display the following *TWO* *questions if immigrant = 1 (this is conditioned bsaed on our original information on PhD students)*

2. How would you rank the following factors in influencing your decision to enroll in a PhD in the US specifically? *Please drag each option up or down to reflect their order of importance, with the top (1) = most important and the bottom (4) = least important.*

________ Industry career opportunities in the US after graduation (1)

________ Academic career opportunities in the US after graduation (2)

________ Quality and reputation of US institutions (3)

________ Connection to faculty in a US institution (4)

. . . .

If any important factors were missed above, please write them here.

____

3. What factors influenced which PhD programs you applied to, and ultimately which PhD program you enrolled in? *Please drag each option up or down to reflect their order of importance, with the top (1) = most important and the bottom (5) = least important.*

_________ University/department's overall ranking or academic reputation (1)

_________ Personal preference for a specific location or region (e.g., proximity to family, climate, cost of living) (2)

_________ Opportunity to work with a particular advisor (3)

_________ University/department/advisor's industry connections or partnerships (4)

_________ Career placement record and outcomes of previous PhD graduates (5)

. . . .

If any important factors were missed above, please write them here.

____

4. Did you select your advisor before or after starting your PhD program?

☐ Before joining

☐ After joining

☐ Can't recall/not sure/other

display the following question if "Before joining" is selected in the last question

4a. Did you know your advisor before starting your PhD program?

☐ No

☐ Yes

display the following question if "Yes" is selected in the last question

4b. Where and how did you meet your advisor?

____

5. How did you decide on your PhD advisor(s)? *Please select the top (up to) three most important factors.*

☐ Shared cultural background, cultural familiarity, or language considerations (if applicable) (1)

☐ Advisor's industry connections (e.g., relationships with companies, potential for internships or post-PhD positions) (2)

☐ Advisor's academic connections (e.g., collaborations with other researchers, access to prestigious networks) (3)

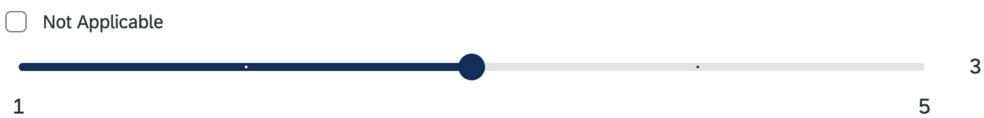
☐ Advisor's reputation in the field (e.g., prominence, citation impact) (4)

☐ Mutual connection or shared professional network (5)

☐ Alignment with my research interests (e.g., expertise in my area of focus) (6)

. . . .

5a. If applicable, how important was the shared ethnic or cultural background of your advisor in your decision-making process? *(Scale: 1=none, 5 = significant)*



6. When you began your PhD, what type of job did you plan to pursue after graduation? *(Select all that apply. If you didn't have a preference select both)*

- ☐ Industry (e.g., start-ups, tech companies) (1)
- ☐ Academia (e.g., postdocs, tenure track positions) (2)
- ☐ Other (e.g., government, national labs, non-profits). Please specify: (3)

  ____

. . . .

7. Did your career plans change after you started your PhD? (i.e., did you start out being interested in academia and become more interested in industry, or vice versa?)

- ☐ Yes (1)
- ☐ No (2)

(display the next question if "Yes" is selected in the last question)

Please elaborate further on why and how your career plans changed.

____

For the next set of questions, please consider only your first job:

8. What types of positions did you apply for? *(Select all that apply)*

- ☐ Industry (e.g., start-ups, tech companies) (1)
- ☐ Academia (e.g., postdocs, tenure track positions) (2)
- ☐ Other (e.g., government, national labs, non-profits) Please specify: (3)

  ____

. . . .

9. In which sectors did you receive job offers? *(Select all that apply)*

- ☐ Industry (1)
- ☐ Academia (2)
- ☐ Other (please specify): (3)

  ____

10. Please select the top (up to) three most important factors for choosing your first job after your PhD.

- ☐ Salary (1)
- ☐ Advice from my advisor (2)
- ☐ Location of position (e.g., proximity to family, cost of living) (3)
- ☐ Existing connections or relationships within the organization (e.g., internship experience, coauthors) (4)
- ☐ Alignment with my research interests or topical fit (5)
- ☐ Prestige of the position (e.g., academic reputation, industry visibility) (6)
- ☐ Available resources (e.g., funding, access to facilities, research support, computing power) (7)
- ☐ Flexibility of position (e.g., remote work options, work-life balance, adaptable schedules, multiple offices) (8)
- ☐ Fit with the professional environment (e.g., organizational culture, team dynamics, creative independence) (9)

If any important factors were missed above, please write them here.

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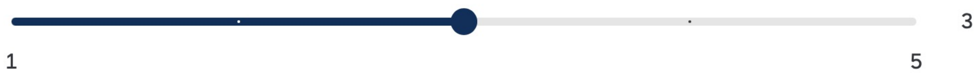
11. How much influence did your PhD advisor have on your post-PhD job decisions? *(Scale: 1=none, 5 = significant)*



display the following *<u>TWO</u>* *questions only if answer to last question is greater or equal to 2*

12. How did your PhD advisor influence your choice of post-PhD job? *(Select all that apply)*

☐ Encouraged pursuing academic roles (1)

☐ Provided academic networking opportunities (e.g., conferences, introductions to academic coauthors and researchers) (2)

☐ Guided my research towards more theoretical questions (3)

☐ Encouraged pursuing industry roles (4)

☐ Guided my research towards industry applications (5)

☐ Provided industry networking opportunities (e.g., introductions to industry professionals, alumni, or coauthors) (6)

☐ Facilitated industry internships (7)

. . . .

13. If you would like to elaborate further on how your PhD advisor influenced your career, please comment here.

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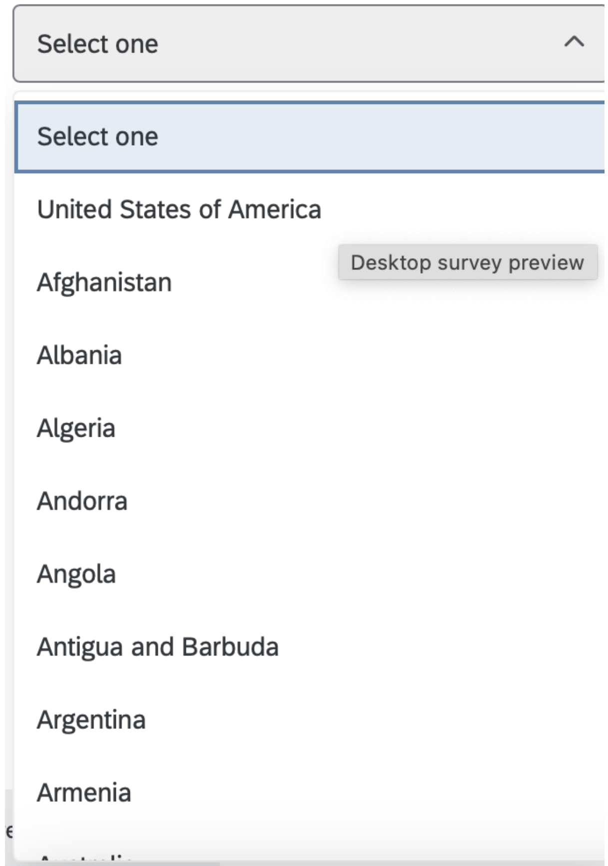
What country did you spend most of your childhood in?



We are seeking individuals to interview over Zoom regarding their experiences with their PhD and early career. If you would be interested in talking with us about your experiences, please enter your email below. Your interview responses will be kept confidential.

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