Mapping the Institutional Pipeline for Global AI Talent*

Caroline Fry[1] and Britta Glennon[2,3]

[1]Shidler College of Business, University of Hawaii at Manoa
[2]The Wharton School, University of Pennsylvania
[3]NBER

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Abstract

Immigrants play a central role in U.S. frontier AI, yet the institutional pathways that bring them into these positions are not well understood. This paper examines U.S. universities as key conduits linking global talent to domestic firms. Using data on 1,757 AI graduates from top U.S. PhD programs alongside surveys and interviews, we show that immigrant students, particularly from Asian low- and middle-income countries, not only leverage PhD programs to enter into U.S. firms, but also have different experiences during the PhD from their native counterparts. They are more likely to have diaspora, or conational, advisors, pursue advisor-facilitated industry internships during their PhD, and hinge from these internships into their first jobs in elite AI firms. Our findings reveal a structured pipeline: universities, diaspora faculty and advisor industry networks collectively channel global talent into a small set of U.S. frontier firms, highlighting universities' dual role as educators and gateways for high-skill migration.

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1 Introduction

Recent hires in top artificial intelligence (AI) firms have drawn intense attention for their influence and market value—likened by the New York Times to "NBA stars" of the technology world (New York Times, 2025). Despite AI's global scope, its most productive researchers remain strikingly concentrated in the United States: in 2022, more than half of the world's elite AI researchers were based in California alone, compared to just one in ten in China (Economist 2025). Many of these frontier researchers are immigrants, particularly from India and China; roughly two-thirds of Silicon Valley's tech employees were foreign-born (Silicon Valley Index 2022). Yet while the prominence of immigrants in U.S. frontier AI is widely recognized, far less is understood about the institutional pathways that bring them into these roles. What channels connect foreign talent to doctoral training in the United States, and from there into the country's most advanced technology firms?

This paper examines that channel of global talent into the U.S. AI industry. We focus on U.S. universities—and in particular, doctoral programs—that form a central institutional bridge linking global supply and domestic demand for AI researchers. Doctoral programs provide lawful entry through student visas (the F-1 and subsequent OPT extensions), exposure to frontier research, and access to professional networks that connect academia and industry (Bound et al., 2015; Amornsiripanitch et al., 2021; Bound et al., 2021). Immigrants often face structural constraints, such as restrictive visa policies and limited domestic social capital, that make university institutions and advisors especially important in guiding their transitions into the U.S. labor market. Prior research shows that early career experiences, particularly during doctoral training, exert long-lasting effects on scientists' professional trajectories (Azoulay et al., 2017; Roche, 2023; Gaulé and Piacentini, 2018). Within these programs, faculty advisors act as gatekeepers and sponsors, selecting, training, and credentialing future researchers. When advisors share students' national backgrounds, co-ethnic networks can facilitate the mobility and advancement of immigrant scientists by transmitting information, trust, and opportunities across borders (Azoulay et al., 2017; Kalnins and Chung, 2006; Kerr and Mandorff, 2023; Freeman and Huang, 2015; Marinoni, 2023; Nanda and Khanna, 2010). In this sense, diaspora faculty operate as cross-border brokers—linking foreign education systems to U.S. universities and, through them, to industry opportunities.

To examine how these institutional and social mechanisms operate in practice, we combine rich longitudinal data with original surveys and interviews to trace these pathways empirically. Using a dataset of 1,757 graduates from top U.S. AI PhD programs between 2014 and 2018, collected by the Center for Security and Emerging Technology (CSET), we link students' educational and career histories to the backgrounds of their advisors and to publications. We then draw on original surveys and interview evidence to unpack the mechanisms of advisor matching, doctoral training, and early-career employment. Together, these sources allow us to trace the steps of this conduit: from their home countries to doctoral training to early-career employment in frontier firms.

The pathway we document can be illustrated by the experience of Ji Lin, who completed his undergraduate studies in China before pursuing a PhD in computer science at MIT under Professor Song Han (himself Chinese-born). During his doctorate, Lin collaborated extensively with industry partners and later joined Nvidia and OpenAI, contributing to projects such as GPT-4. His trajectory—from home-country undergraduate education, through U.S. doctoral training with a diasporic advisor embedded in industry networks, to employment in frontier AI firms—captures how universities, visa policy, and diaspora networks jointly structure the movement of global talent into the U.S. innovation system.

This paper offers an empirical person-level description of that conduit. We show, first, that immigrant students, especially those from Asian low- and middle-income countries (LMICs), are roughly 13-15 percentage points more likely than U.S. natives to be paired with advisors from their same national or regional background. These patterns hold even after controlling for student productivity, prior industry experience, and advisor quality, indicating that they do not simply reflect institutional composition or advisor availability. Survey and interview evidence suggests that these matches arise through diaspora networks built on reputation, prior contact, and shared culture that connect talent in Asia to U.S. universities.

Second, immigrant students—particularly those from Asian LMIC countries—experience doctoral training that is distinctly more industry-oriented than that of their U.S. peers. They are roughly 22 percentage points more likely than natives to undertake an industry internship during the PhD and about 14 percentage points more likely to do so in a top AI firm. This elevated engagement reflects not only individual initiative but also the networks of their advisors. Students whose advisors have stronger industry collaborations are significantly more likely to secure internships, with this effect especially pronounced for Asian LMIC students. Survey evidence reinforces this pattern: 18 percent of Asian LMIC respondents reported that their advisor directly facilitated an internship, compared to 13 percent of U.S. natives and only 2 percent of other immigrants. The influence of advisors' professional networks is most visible in departments and universities with weaker formal industry linkages—particularly outside top-ten institutions and beyond computer science—where personal connections substitute for institutional pathways. Taken together, these findings suggest that immigrant students, and Asian LMIC students most of all, rely heavily on advisor networks to access industry-facing opportunities during doctoral training.

Third, these differences in doctoral experiences extend into employment outcomes. Asian LMIC students are roughly twice as likely as U.S. natives to take first jobs in elite AI firms, with internships serving as their principal bridge to employment. Survey and interview data confirm that advisors often mediate these transitions, connecting students to companies and signaling their capabilities to recruiters.

Taken together, these findings depict an institutionalized system through which the economic pull of the U.S. AI ecosystem, the legal framework of student and work visas, and the relational networks of diaspora faculty combine to channel global talent into a small number of U.S. organizations. Rather than a spontaneous flow of individual migrants, the movement of elite AI researchers follows a structured path, sustained by recurring linkages between sending-country universities, U.S. doctoral programs, and frontier

firms.

Theoretically, this phenomenon connects three literatures that are rarely integrated. A large body of research has examined the contribution of immigrant scientists to innovation, entrepreneurship, and firm performance (e.g., Stephan and Levin, 2001; Beerli et al., 2021; Brinatti et al., 2023; Glennon et al., 2024; Hunt, 2011; Bernstein et al., 2022), yet this work typically treats the supply of immigrant talent as exogenous to firms. The economics of skilled migration emphasizes wage differentials and visa policy as the main drivers of high-skill mobility, focusing on individual incentives rather than the institutional or relational channels through which talent moves (e.g., Grogger and Hanson, 2011; Bound et al., 2015, 2021). Research on homophily and diaspora networks highlights relational mechanisms of trust and information but rarely embeds them in institutional contexts or considers how they interact with immigration regimes (Freeman and Huang, 2015; Kerr and Mandorff, 2023; Nanda and Khanna, 2010; Dustmann et al., 2016). Finally, organizational scholarship on pipeline hiring shows how firms recruit through established educational and professional channels but typically treats those pipelines as domestic (e.g., Brymer et al., 2024). Our analysis shows that these processes intersect: global talent pipelines emerge where economic incentives, legal access, and network ties align.

By tracing the operation of this pipeline in AI, we reveal how universities perform a dual role as educational institutions and gateways for global talent. They import and credential right-tail talent, embed it in industry-linked research networks, and export it into U.S. firms. For firms, this dynamic represents a vital—and often overlooked—channel for accessing high-skill immigrant talent. Disruptions to this pipeline, whether through restrictions on international student access or limits on immigrant faculty advising, could constrain firm-level innovation and reduce the flow of specialized talent into key sectors. Understanding this mechanism is essential not only for explaining the composition of the AI workforce but also for theorizing how institutional structures mediate global knowledge and human capital flows.

2 The Economic and Policy Forces Shaping Global AI Talent Flows

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, trained on enormous datasets using custom-built hardware, simultaneously set academic benchmarks and underpin new products. Because frontier progress depends on computer infrastructure and data at a scale unavailable and unaffordable to most governments or universities, the largest and most sophisticated AI models are typically the product of industry or industry-university collaborations (Ahmed et al., 2023). This overlap of basic and applied research makes industry central to AI

advancement, as both the primary funder of compute and data and a key research partner to universities.

According to recent international industry and investment reports, the United States – and U.S. firms in particular – are at the forefront of artificial intelligence innovation (Maslej, 2025; AIPRM, 2024). The dominance of U.S. industry is particularly visible in computing power and data. Training state-of-the-art AI models requires 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 such as Amazon, Microsoft, and Google 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. Companies like Google and Meta collect billions of user interactions daily, generating data streams that underpin their advances in natural language processing, vision, and generative AI.

These structural advantages are amplified by geography and funding. Silicon Valley remains one of, or the world's leading technology cluster, not only in AI but also in semiconductors, software, and venture capital (e.g., Kerr and Robert-Nicoud, 2020; Organization, 2024). Rival clusters in China, the EU, and the Gulf are growing, but they lack the decades of accumulated capital, firms, and human networks that make Silicon Valley singular. The financial scale of the U.S. ecosystem is also unmatched: as an example, Alphabet (the parent of Google) alone spent $1.5 billion on its subsidiary DeepMind in 2021, as compared to the $1.2 billion spent by the European Commission in the same year (Ahmed et al., 2023).

PhD-level talent is the third critical input, for which the United States exerts disproportionate pull. Companies in the United States offer AI researchers salaries roughly double those of their foreign counterparts, not including stock options and the future draw of escalating pay scales (Economist, 2025). By 2022, more than half of the world's elite AI researchers were based in California, compared to just one in ten in China. This concentration of advanced human capital reflects not only wage incentives but also the agglomeration of research infrastructure and firm–university linkages that make the U.S. AI ecosystem uniquely attractive.

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

The global distribution of AI talent reflects powerful economic push–pull dynamics. 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. Borjas (1987) formalized how wage gaps and migration costs shape the self-selection of migrants by skill, and subsequent work demonstrates that educated immigrants are especially responsive to host-country economic and institutional conditions. Hunt (2011) and Bound et al. (2015) show that foreign-born scientists and engineers disproportionately enter U.S. STEM fields when domestic opportunities expand, while Abramitzky and Boustan (2022) find that immigrants are more likely than natives to move to high-opportunity places. In short, migration flows reflect the interaction of pull forces (wages, research opportunities, and institutional access) with push

forces that constrain the returns to skill at home (e.g., Jenkins, 1977; Van Hear et al., 2018).

These economic forces intersect with the rapid expansion of higher education in Asia and other emerging regions. Over the past two decades, tertiary enrollment in science and engineering has grown dramatically. China's 1999 higher education reform alone increased annual college admissions nearly tenfold—from about 1 million in 1998 to over 9 million by 202—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; Foundation, 2023). Yet these quantitative expansions outpaced growth in research infrastructure and advanced training capacity. In China, mid- and lower-tier institutions accounted for most of the new seats, while doctoral and postdoctoral programs expanded only modestly (Jia et al., 2025). In India, only a small fraction of engineering and computer-science graduates gain entry into elite Institutes of Technology or research universities (Bound et al., 2021).

The consequence has been a surplus of technically trained workers in these countries relative to domestic research and high-tech employment opportunities. Despite the surge in STEM education, AI-relevant research infrastructure—large compute clusters, proprietary datasets, and venture-capital-backed firms—remains concentrated in a few metropolitan areas in high-income countries. Bound et al. (2021) document that while the number of Chinese students enrolled in U.S. universities increased sixfold between 2005 and 2019, this rise was driven by a swelling cohort of domestic STEM graduates unable to find commensurate opportunities at home. Jia et al. (2025) estimate that every additional 100 college graduates produced by China's expansion generated 3.6 new Chinese graduate students in the United States, with effects strongest in STEM fields. This imbalance between mass undergraduate expansion and limited advanced research absorption has created what they term "ripple effects" across the global education system: large origin-country surpluses of college-educated engineers have spilled into foreign graduate programs, particularly in the United States.

The global market for AI talent exemplifies the combined effects of these strong pull and push dynamics, resulting in sustained flows of AI researchers to the United States. Much of the U.S. AI workforce now comes from abroad, especially Asia. Two-thirds of the tech workforce in Silicon Valley is foreign-born, with immigrants from India and China alone accounting for over 40 percent of all workers in the region (Valley, 2025). For researchers in Asia and elsewhere, the United States offers not only higher pay but also unrivaled access to the networks, infrastructure, and opportunities that define the global AI frontier. As the next subsection details, universities play a central role in translating these incentives into realized migration, serving as the institutional bridge that connects global talent supply to U.S. labor demand.

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 employers select and sponsor workers, but that pathway is tightly rationed and highly uncertain at

the point of labor market entry. By contrast, the student route is comparatively accessible and temporally flexible. Together, these features position U.S. PhD programs as a reliable "legal ladder" into the American AI sector: they offer lawful entry (F-1), time-limited work authorization after graduation (OPT and the STEM-OPT extension), 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. The contrast between student and work visas is stark. 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; when adjudication becomes stricter, top-scoring students reduce SAT taking, score sending, and U.S. enrollment (Chen et al., 2023). Critically, students' decisions to study in the United States are strongly influenced by whether they expect to work there afterwards: when the H-1B cap was reduced in 2003, both international enrollment (Shih, 2016) and the quality of the applicant pool declined (Kato and Sparber, 2013), reinforcing the view that students pursue U.S. study not only for education itself but because universities provide the main pathway into American industry. It also gives international enrollees the ability to undertake "Optional Practical Training" without employer petitioning; 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, unlike 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, creating additional scope for students and postgraduates to remain employed in academic or affiliated settings while seeking private-sector sponsorship. Recent evidence demonstrates that the central role of universities in channeling foreign STEM talent into U.S. employment arises at least in part from the structure of U.S. visa policy, which restricts direct work entry while keeping student routes comparatively open. Bound et al. (2015) show that by 2010, nearly half of all foreign IT professionals working in the United States had first entered on student visas, and that roughly 30 percent of foreign graduates initially transition into the labor market under OPT before seeking H-1B sponsorship. Using linked administrative data, they find that U.S. degree holders are both more likely to remain in the country and more likely to secure employment than those educated abroad, reflecting the signaling and access advantages of U.S. credentials. Similarly, Amornsiripanitch et al. (2021) show that the majority of immigrant founders of VC-backed firms first came to the U.S. for higher education.

Beyond serving as a legal gateway, American institutions also anchor the institutional and research networks that connect global talent to frontier firms. U.S. universities not only dominate global rankings in computer science and engineering (Symonds, 2025) but also function as central nodes linking research and industry. AI departments at leading universities routinely collaborate with firms through sponsored re-

search projects, joint labs, and dual academic–industry appointments.[1] Doctoral students are 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, transforming universities into both entry points and institutional bridges within the U.S. AI labor market.

In practice, this makes universities a legal and an organizational gateway into U.S. industry. For firms, recruiting top AI talent directly from abroad is costly and uncertain: H-1B sponsorship is capped, administratively costly, and subject to lottery uncertainty, while evaluating candidates trained overseas involves substantial information frictions. By contrast, students who arrive on F-1 visas and train in U.S. PhD programs are both legally present and institutionally vetted. Doctoral training provides firms with observable signals of quality through publications, internships, and faculty recommendations, while OPT and STEM-OPT give employers a trial window of up to three years without committing to cap-subject sponsorship. At the same time, universities "import" right-tail talent at the point of admission, embed students in joint labs, sponsored projects, and internships during training, and provide cap-exempt roles or transition windows after graduation. provide an institutionalized pathway and organize the recruitment, training, and placement of foreign scientists, linking immigration policy to labor-market outcomes. Through their dual role as educational institutions and visa sponsors, universities shape how international talent is selected, socialized, and ultimately absorbed into the U.S. innovation system.

3 Framing Questions and Conceptual Motivation

In this section, we draw on existing research to develop a conceptual framework for understanding how universities shape the participation of immigrant researchers in the U.S. AI pipeline.

3.1 Advising Relationships as Institutional Matching Mechanisms

Doctoral advising is a critical organizational relationship in graduate education, linking the process of recruitment, training, and placement. A large literature shows that advisor characteristics such as research orientation and gender shape students' productivity and career trajectories (Azoulay et al., 2017; Roche, 2023; Gaule and Piacentini, 2018). Advisors act as both evaluators and sponsors, mediating access to information, funding, and professional networks.

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 (Foundation, 2023). For these applicants, prior credentials, letters, and institutional reputations are often difficult for admissions committees to interpret. Faculty judgments therefore play a pivotal role in assessing quality and

[1] 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.

fit, translating heterogeneous educational signals into evaluations that domestic committees can compare. Once students arrive, advisors continue to shape how they navigate linguistic, cultural, and institutional barriers, becoming the primary interface through which individual potential is recognized, cultivated, and certified within the academic system.

Hence, advising can be understood as a matching process embedded in organizational and global contexts. Departments must evaluate applicants from heterogeneous education systems, while prospective students must infer the quality, mentoring style, and professional reach of potential advisors. Under such uncertainty, networks and prior social ties help to reduce matching frictions (Brymer et al., 2024).

Diaspora faculty occupy a distinctive position as intermediaries between foreign and domestic academic systems. Having navigated both origin country and U.S. academic institutions, they possess contextual knowledge about foreign education systems, grading norms, and research cultures. This knowledge allows them to interpret educational signals that may be opaque to domestic colleagues and, in some cases, to identify or recruit promising students through professional networks abroad. At the same time, from the student's perspective, diaspora faculty provide trusted points of entry into the U.S. academic system. Much like the mentoring relationships analyzed by Azoulay et al. (2017); Roche (2023), in which trainees internalize advisers' orientations not deliberately sought at the time of matching, diaspora advising may transmit professional norms, aspirations, or network ties beyond those initially motivating the advisor–student connection. Such network-based matching mechanisms align with evidence that recruitment through shared group ties or repeated interactions—so-called "pipeline hiring"—can enhance match quality when information is incomplete (Dustmann et al., 2016; Åslund et al., 2014; Brymer et al., 2024).

At the same time, relational and cultural mechanisms reinforce these informational channels. Shared language, trust, and familiarity can facilitate communication and collaboration in apprenticeship-style training. Advisors and students who share background or cultural reference points may find it easier to exchange tacit knowledge and sustain close mentoring relationships. Empirical work on gender-matched advising (Gaulé and Piacentini, 2018) and on ethnic homophily in collaboration and entrepreneurship (Kerr and Mandorff, 2023; Freeman and Huang, 2015) supports the idea that identity proximity can foster effective mentoring and knowledge transfer. More broadly, research demonstrates that coethnic networks shape outcomes in a variety of other domains: entrepreneurship (Kalnins and Chung, 2006; Kerr and Mandorff, 2023; Marinoni, 2023; Nanda and Khanna, 2010), multinational companies (Hernandez and Kulchina, 2020), trade (Rauch and Trindade, 2002), location choice (Bauer et al., 2005; Cadena et al., 2017), hiring (Åslund et al., 2014; Kerr and Kerr, 2021a), and postdoc mentor pairing (Azoulay et al., 2017). These findings collectively suggest that shared identity can operate as a form of social capital that lowers asymmetric information, facilitates trust, and sustains repeated cooperation across borders.

In the doctoral context, these mechanisms imply that diaspora advisors may act as bridges connecting geographically distant human capital to U.S. universities. By channeling information, trust, and reputation, they can substitute for missing institutional signals and enable recruitment from a broader range of global

talent pools. Yet, we lack systematic evidence on whether and how diaspora advisors shape who gains entry and training through U.S. AI doctoral programs.

This conceptual gap motivates our first framing question,

> **Framing Question 1:** How do diaspora faculty facilitate the movement of foreign-trained students into U.S. AI doctoral programs?

3.2 From Training to Employment: Universities as Industry Pipelines

If doctoral advising determines who enters graduate programs, the training environment determines how students engage with the scientific and industrial frontier both during and after the PhD. 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).

Advisors, departmental norms, and university–industry linkages jointly shape what students learn, the professional networks they access, and the sectors in which they eventually work. 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 embedded in these environments may participate in industry-funded research, contribute to open-source software used in commercial systems, and undertake internships that double as extended job auditions. In this sense, doctoral students may move seamlessly between academic labs and industrial research groups. The PhD therefore functions both as a credentialing process and as an institutional channel that connects universities to firms.

Within this system, advisors and departmental practices operate as the micro-mechanisms translating university structures and professional networks into individual career outcomes. Advisors with industry collaborations may channel students toward coauthored research, data access, and internships, while those oriented toward academic publishing have academically-oriented reputational and network capital (Roche, 2023; Azoulay et al., 2017). Organizationally, such linkages create cumulative advantages: departments and advisors with strong corporate partnerships can offer richer training and more visible placement pipelines, attracting further sponsorship in turn. The structure of doctoral training thus embeds labor-market pathways directly into the process of scientific production (Stephan, 2012).

Immigrant doctoral students enter these environments with distinctive preferences and opportunity sets. Migration economics suggests that migrants are positively selected on both ability and ambition (Borjas, 1987; Grogger and Hanson, 2011; Glennon et al., 2024), and that they often view foreign study as a vehicle for upward mobility and access to frontier technology (Bound et al., 2015; Hunt, 2011). In addition,

immigrants bring distinct knowledge endowments shaped by geographically specific technological specializations (Bahar et al., 2014, 2020; Branstetter, 2001; Keller and Yeaple, 2013) and comparative advantage in technical, research-intensive tasks (Peri and Sparber, 2009; Mayda, 2022). They also seem to exhibit stronger commercialization tendencies, potentially driven by economic constraints or barriers in securing funding within traditional academic routes (Roach et al., 2019).

At the same time, immigrants face structural constraints that can reinforce or counteract those preferences. Temporary visa holders must navigate limited post-graduation work windows under OPT and the capped H-1B lottery. Because universities are exempt from visa caps and provide legally authorized employment, academic paths may appear less risky, whereas large firms with established sponsorship programs offer alternative security (Kahn and MacGarvie, 2020; Roach and Skrentny, 2019). Empirical evidence remains mixed: Amuedo-Dorantes et al. (2019) find that stricter visa caps pushed international graduates toward academia, while Kahn and MacGarvie (2020) report little difference in sorting between academia and industry among Chinese and Indian PhDs despite differences in green card wait times.

Given differences in preferences and constraints, immigrant students are also likely to experience doctoral training differently from their native peers. Theories of migration and network dependence suggest that migrants rely more heavily on institutional and interpersonal networks to navigate host-country labor markets (e.g. Dustmann et al., 2016; Kerr and Kerr, 2021b). Often lacking domestic reference points and social capital, they may depend more on university structures to acquire both information and legitimacy. Analogous dynamics are well documented in the broader immigration literature: because immigrants often face informational asymmetries, limited job-market recognition, and barriers to mainstream networks, they turn to coethnic employers and ethnic enclaves (e.g., Borjas, 1986). These studies show that immigrants use social and institutional ties to overcome deficits of local information and reputation—mechanisms that closely parallel those operating within universities.

Important gaps remain in understanding how these processes unfold within doctoral training and whether they operate differently for immigrant students. Existing research has shown that advisor characteristics influence publication output and career orientation (e.g., Roche, 2023; Azoulay et al., 2017; Gaule and Piacentini, 2018), but we know less about how advisors' professional networks intersect with students' immigrant status. Likewise, while migration scholarship highlights the role of networks in labor-market integration (e.g., Kerr and Mandorff, 2023; Nanda and Khanna, 2010; Marinoni, 2023), it rarely examines how such mechanisms function inside academic organizations or how they interact with the distinctive structure of doctoral programs. Existing explanations focus largely on visa constraints, overlooking other factors that might influence immigrant students' transitions into industry from doctoral programs.

Building on these insights, our analysis focuses on two additional framing questions,

> **Framing Question 2:** How do immigrant students' doctoral experiences unfold within the AI training environment?

This question emphasizes the institutional and relational mechanisms—advisors, internships, and uni-

versity–industry linkages—through which students engage with the frontier of AI research during the PhD.

> **Framing Question 3:** How do these training trajectories influence transitions into top U.S. AI firms for immigrant students?

Together, these questions guide our examination of doctoral training as an institutionalized pathway to the U.S. AI labor market.

4 Data Sources and Measures

4.1 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.[2] 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.[3] Employers are manually categorized into two main groups: academia and industry.[4] 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.[5] 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),[6] and the fifteen best-rated AI employers in 2018, as reported by Forbes (via Glassdoor)

[2] 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.

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

[4] 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.

[5] 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 NRS and QS ranking websites.

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

and Business Insider (Nvidia, Adobe, Microsoft, Tesla, Intel, Spotify, IBM, Snap, Disney, Airbnb, Uber, Accenture, Wells Fargo, Samsung, MoTek Technologies, Lenovo, Rakuten Marketing).[7]

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 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 only about three percent of U.S. undergraduates were immigrant students during our timeframe (Bound et al., 2015). To conduct supplementary analysis we also rely on information on the name nationality of each sample student, using the NamePrism algorithm which assigns the most probable name nationality using the first and last name of each individual.[8]

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).[9] 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 a few key reasons. 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 (Grogger and Hanson, 2011). Second, the magnitude of the Asian talent base makes it uniquely consequential for the global AI labor market. China and India alone account for a large majority of the world's engineering graduates and an expanding share of AI-related undergraduate degrees.[10] Yet both countries' doctoral and industrial research capacities remain constrained relative to their graduate output. Third, the dense academic diasporas that have emerged from these same countries make them critical to understanding how advisor–student networks function. Faculty of Asian origin comprised 35.3 percent of tenured or tenure track computer science faculty in 2018[11] creating the relational infrastructure through which new cohorts of students are identified, recruited, and mentored. If diaspora advisors indeed act as bridges linking foreign talent to U.S., this mechanism will be most observable where both the potential student base

[7] 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

[8] Several studies use name-based measures of ethnicity to study coethnic ties, including Freeman and Huang (2015); Kerr and Lincoln (2010); Kerr (2008). The advantage of NamePrism is its granularity: it produces narrow name nationalities such as "EastAsian,Japan" or "Nordic,Scandinavian,Sweden", rather than broad ethnic groupings.

[9] 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.

[10] See https://www.oecd.org/en/publications/the-supply-demand-and-characteristics-of-the-ai-workforce-across-oecd-countries$_b$17314$a-en.htmlandhttps://unesdoc.unesco.org/ark:/48223/pf$0000394112, $lastaccessed$10.22.25.

[11] See https://ira.asee.org/by-the-numbers/engineering-faculty/ last accessed 10.22.25

and the diaspora network are large. Asian LMICs thus represent not only the primary source of frontier AI talent migration but also the empirical setting in which the broader dynamics of global talent pipelines can be most clearly observed.

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, as defined by the location of their undergraduate degree, with almost 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 the shares of other immigrant hires (12-26%). In these firms, the higher representation of Asian LMIC immigrants corresponds to a smaller relative share of natives, who make up a markedly smaller share of hires than in the overall sample. By contrast, academic employers such as MIT, Stanford, Harvard, and Princeton do not exhibit such overrepresentation, with the balance tilted more towards natives.

[Table 1 about here.]

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 problem. 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 the PhD, during the PhD, 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 publica-

[12] We standardize department names into broad categories.

[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.

tions yields a measure of the extent to which their research topics align more closely with industry- versus academia-oriented work.

4.2 Advisor Details

We 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. Advisors with non-U.S. undergraduate education are classified as immigrants, and, within this group, we distinguish between those from Asian LMIC countries (as defined above) and those from other countries. Information on advisors' undergraduate institutions was collected from department websites and online resumes. 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.

Second, we classify advisors by name nationality using the NamePrism algorithm applied to both first and last names. 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.[15]. 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 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, as identified by OpenAlex. [also top industry coauthors, and unique industry coauthors –and grant data - maybe using – haven't merged yet]

4.3 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.[16]

The survey of PhD students asked questions around program and advisor selection (Q1-5), original career plans (Q6-7), and factors influencing their first job choice (Q8-13). We also asked them about their country of origin to cross-check our own immigrant definition.[17] The survey of advisors asked questions around PhD student selection (Q1) and why they might have ended up going into industry or academia

[15] 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.

[16] See Appendix Table B3 for response rate variation across sample subgroups.

[17] 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.

(Q2-4), as well as questions around how many students they've advised and where they are originally from. Both students and advisors were asked whether they'd be willing to interview with us. We conducted interviews with five individuals between February 26 and March 21, 2025 over Zoom. All survey tools can be found in Appendix B.

4.4 Descriptive Statistics

We first present descriptive evidence on both observed educational and career differences, and on self-reported motivations at the outset of PhD training.

Table 2 shows raw differences across natives, Asian LMIC immigrants, and other immigrant PhD students.[18]

Graduation year does not differ significantly across 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 industry collaborative publications in the five years preceding the 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 students, 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 later.

[Table 2 about here.]

These differences in productivity, advising, and early career outcomes are mirrored by differences in the motivations students report at the outset of their PhD training. According to 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. Further, and as demonstrated in Appendix Figure A1, students from Asian LMIC countries also reported different industry-related goals prior to starting the PhD program.

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

For some, the decision to study a doctorate in the United States was shaped as much by immigration considerations as by professional aspirations. 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. As one respondent put it, the attraction of a U.S. doctorate lay not only in research quality but also in the opportunity to "get an advanced U.S. degree" while establishing a foothold in the country.

These patterns suggest that career preferences vary across groups even before doctoral training begins, suggesting that immigrant students—and particularly those from Asian LMICs—may view U.S. doctoral programs not only as a site of advanced training but also as a structured entry point into industry, consistent with the broader pipeline we describe in this paper. These baseline contrasts in outcomes and motivations set the stage for our analysis of how universities and advisors channel immigrant talent through the U.S. PhD–to–industry pipeline.

5 Analysis and Results

In what follows, we investigate each phase of our proposed pipeline in turn, specifically through the lens of our three primary research questions. First: How do diaspora faculty facilitate the movement of foreign-trained students into U.S. AI doctoral programs? Second: How do immigrant students' doctoral experiences unfold within the AI training environment? And Third: How do these training trajectories influence transitions into top U.S. AI firms for immigrant students?

5.1 Entry and the Role of Diasporic Advisors

The immigrant students in our sample do not arrive in U.S. PhD programs as blank slates. They bring with them distinct preferences and constraints and, as the descriptive evidence already suggested, they are more likely to be advised by immigrant faculty, or those who share their own background. In this section, we examine the entry point into doctoral training and the pivotal role that diasporic, especially conational, advisors play in channeling immigrant talent into U.S. universities.

Figure 1a provides a descriptive overview of the flow of students to advisors by undergraduate country group. Several patterns stand out. Unsurprisingly, most U.S.-educated undergraduates are paired with U.S.-educated advisors. But immigrant students, particularly those from Asian LMIC countries, are far more likely than chance would predict to be paired with advisors who also trained in Asian LMICs. The figure also shows that cross-group advising is common—Asian LMIC students are frequently advised by U.S.-trained faculty, and U.S. students by immigrant faculty—but the overall pattern is nonetheless one of systematic conational matching.

[Figure 1 about here.]

To formalize this evidence, we compare predicted and actual rates of conational advising. The predicted rate assumes random assignment of students to advisors, using the distribution of advisors' undergraduate countries in the sample. 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.[19] We then compute the actual rates of student-advisor pairs by country. Figure 2 plots these predicted and actual match rates for the eight largest undergraduate-origin countries in the sample. Across the board, actual rates exceed predicted rates, indicating that students from China, India, and other Asian LMICs are disproportionately likely to be mentored by advisors who share their national background.

[Figure 2 about here.]

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—for example, arising from disciplinary differences or advisor quality—we turn to regression analysis. Specifically, we estimate the following specification:

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

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 $prePh.Dpubs_i$, 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[20] 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 results. $advisorhindex_i$ 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

[19] 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.
[20] In cases with more than one advisor, the maximum value is taken.

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.

[Table 3 about here.]

In Appendix Table A5, we extend the analysis using advisor name nationality as an alternative measure of conationality. This group may include not only first-generation immigrant advisors but also those who immigrated prior to college or second-generation immigrants. The results again show a strong role for conational connections: Asian LMIC students are 16-18 percentage points more likely than natives to have an advisor with an Asian name nationality, and about 7 percentage points more likely than other immigrants to share the same name nationality with at least one advisor. These findings reinforce that the conational advising pattern is not limited to undergraduate country definitions but also emerges when nationality is measured through names, underscoring the relevance of diasporic networks in shaping student-advisor pairings.

Robustness checks further support this conclusion. Controlling for the number of Asian faculty at each university[21] in the PhD start year rules out the possibility that the pattern simply reflects institutional composition (Table A6 column 2). Restricting the sample to cases where student and advisor come from different Asian countries shows no evidence of elevated matching (Table A6 column 3). Excluding Chinese or Indian students, who make up the largest shares of Asian LMIC immigrants, does not eliminate the effect, indicating that the result is not solely driven by their scale. Finally, the results remain similar when excluding non-science and engineering students, who may have different selection criteria for PhD programs or advisors (Table A4).

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 Table A7, immigrant faculty overall are about 13 percentage points more likely to advise immigrant students, but the effect is concentrated among Asian LMIC faculty. They are over 23 percentage points more likely to supervise at least one Asian LMIC student specifically, and more than 30 percentage points more likely to supervise at least one student from their own home countries, particularly Asian LMIC immigrant faculty. By contrast, other immigrant faculty show no similar tendency.

Table A8 reinforces this pattern using a dyad-level approach, in which each student is paired with every potential advisor within the same field, measured using department names, (and, in extended specifications, within the same field and institution). This design allows us to compare realized advisor-student

[21] We obtain the number of Asian faculty at each university from the IPEDS NCES database.

pairings against all possible pairings within the relevant pool of faculty.[22] The results show that realized matches are systematically skewed toward conational pairings. The relationship persists even after controlling for whether students and advisors share a commercial orientation or similar levels of academic productivity (columns 2, 4, and 8). It is instead driven by shared country of origin: student-advisor pairs with a common undergraduate country are significantly more likely to form, with the relationship especially strong for immigrant students (columns 3, 4, 7, 8). Results confirm the prevalence of conational matching even after accounting for the advisor options available to each student and student options for each advisor, with particularly strong effects for immigrant students.

So, in sum, conational, or diasporic, advisors play an important role in attracting and training immigrant students, especially those from Asian LMIC countries. For these students, conational advisors constitute a critical point of entry into U.S. doctoral programs, reinforcing our broader argument that universities, and the faculty within them, act as institutional gateways connecting global talent flows to elite positions in U.S. AI.

5.1.1 Mechanisms of matching: survey and interview evidence

The regression results 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 why these patterns emerge, we draw on survey responses and qualitative interviews with both students and advisors. Whilst we find limited evidence that students, and particularly Asian LMIC students, are matching with advisors because of industry contacts that advisors have (Appendix Table A8 and Appendix Figure A2), we do find some supportive evidence on plausible mechanisms driving these matches. Taken together, the evidence points to three primary mechanisms underlying conational matching: (1) prior personal contact between students and advisors, (2) reputational spillovers within home-country academic networks, and (3) preferences for shared cultural or linguistic background.

Prior contact and familiarity before arrival. Survey results indicate that immigrant students are more likely than natives to have interacted with their advisors in some capacity prior to arriving in the United States. 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.

These findings point to a distinctive recruitment channel for immigrant faculty. Advisors from abroad are more likely to visit their countries of origin for collaborations, conferences, or personal reasons, creating opportunities for early contact with prospective students. Such encounters often seem to lay the ground-

[22] We do not further disaggregate immigrant groups in the dyad specification. Because the model expands the data to all possible student-advisor pairs, groups with very different underlying sizes generate very different numbers of dyads, making coefficient magnitudes across subgroups difficult to interpret.

work for advising relationships that later formalize during admissions. In interviews and survey responses, students described brief but influential interactions that initiated their connections with 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.

Reputational spillovers and visibility through home-country academic networks. A second mechanism appears to operate through reputation and visibility within academic networks abroad. As shown in Appendix Figure A2, over 70% of Asian LMIC immigrant students selected "Advisor's reputation in the field" as an important factor in advisor selection (compared to around 50% of native and other immigrants). Importantly, these reputation effects appear to be geographically specific: U.S. universities and faculty differ in their visibility across regions depending on historical training flows and academic networks.

Interviews and open-ended survey responses consistently emphasized that students learned about U.S. programs and advisors through academic mentors in their home countries—often individuals who themselves had obtained PhDs in the United States. As one respondent explained, their knowledge of U.S. institutions came *"through academic mentors/advisors in my home country."* Another noted that *"Mentors/advisors in home country were also PhD graduates from reputed U.S. institutions"*. In some cases, these reputational ties spanned academic generations: professors at home recommended specific U.S. faculty who had previously trained students from the same institution or who maintained ongoing collaborations with domestic researchers. One interviewee noted that their mentor, a U.S.-trained professor, had helped them to identify which PhD programs to apply to based on their familiarity with departments and faculty. As the student recalled, *"my internship mentor...helped me pick out good faculty who were publishing a lot in this area. He knew about them through publications and through personal connections...many of the faculty he pointed me to were his former peers or students"*. Indeed, the program they ended up attending was the same one their mentor had attended.

These accounts illustrate how diasporic academic networks create reputational pipelines that make certain conational advisors more visible and attractive to prospective students. This reputational mechanism also helps explain why the conational matching pattern persists even after controlling for advisor productivity, quality (h-index), and industry orientation: it operates through information flows and recognition, not through advisor characteristics observable in U.S. academic metrics.

Shared cultural background and affinity. Finally, shared cultural or linguistic background appears to strengthen the relationships between advisors and advisees. 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 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."*. Advisors echoed this theme. One advisor wrote, *"There is a somewhat shared set of issues and concerns and language framework."*, describing how common background facilitated communication and trust.

Another observed that *"International professors who are familiar with those international schools often will also hire from places where they have that deep knowledge."*

Overall, the survey and interview evidence confirms that conational advisor matching among immigrant students—especially those from Asian LMICs—is shaped by a combination of informational and social mechanisms. Prior contact provides a pathway of access, reputational spillovers in home-country academic networks channel information toward known advisors, and shared background strengthens mentoring relationships once established.

These dynamics also help explain why Asian LMIC students constitute such a large share of the AI PhD population—and, ultimately, of the AI workforce. The presence of a sizable faculty diaspora from these same countries creates enduring linkages that connect talent in Asia to U.S. doctoral programs. In effect, conational faculty act as bridges that sustain a recurring pipeline of students from their home countries into U.S. universities, and from there into leading technology firms.

Stylized finding 1: Immigrant students, especially those from Asian LMICs, often pair with diaspora advisors. These matches emerge through faculty diaspora networks—built on reputation, prior contact, and shared culture—that bridge talent in Asia to U.S. universities and firms.

5.2 University Pathways and Industry Transitions

Having shown that diaspora faculty play a central role in shaping the entry of immigrant students into U.S. doctoral programs, we next examine how the PhD experience itself differs across student groups, and how these differences map onto early career trajectories. Whereas the prior section focused on who advises whom, this section documents variation in what students do during their PhDs, and how these patterns translate into distinct pathways into the labor market. To capture these patterns, we estimate the following descriptive specification:

$$Y_i = \beta_0 + \beta_1 Immig_i + \beta_2 prePhDpubs_i + +\beta_4 preIndustryJob_i + \delta_{gradyear} + \gamma_{institution} + \sigma_{dept} \tag{2}$$

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, or obtaining an industry job post-graduation. $Immig_i$ 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.

5.2.1 Internships and industry-linked experiences during the PhD

Table 4 summarizes patterns of industry engagement during the PhD, as measured through internships. 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 2-3 further disaggregate immigrant by country of origin, showing that this difference is largely driven by Asian LMIC students. They 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. Columns 6-7 show that 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. Appendix Table A9 provides complementary evidence using publication-based measures of industry orientation. Columns 1-2 report the likelihood of coauthoring with industry-affiliated researchers during the PhD, while columns 3-4 measure the share of a student's publications that are industry-oriented. 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). Appendix Table A10 similarly examines the industry orientation of their advisors, documenting that on the whole, immigrant, and especially Asian LMIC students have advisors with more industry collaborations, especially with researchers from top AI firms.

Taken together, Tables 4 and appendix Table A9 show that immigrant students—particularly those from Asian LMIC countries—are more integrated into industry networks during their doctoral studies. These differences are visible across multiple indicators: internships, coauthored publications, and advisor linkages. They suggest that for this group, the PhD serves as a structured point of contact with the private sector, offering early exposure to industry research environments and opportunities for post-graduation employment.

[Table 4 about here.]

Advisor ties and internship opportunities Although earlier sections showed that conational matching is not necessarily driven by industry links, advisors' professional networks nonetheless shape students' exposure to industry. Columns 4 and 8 of Table 4 show that the relationship between advisors' industry collaborations and students' likelihood of undertaking internships is stronger for immigrants—particularly Asian LMIC students—than for natives. In other words, advisors' industry connections appear to translate into internships more frequently for immigrant students.

Survey evidence reinforces this finding. As shown in online appendix Figure A4, Eighteen percent of Asian LMIC students reported that their advisor facilitated an industry internship, compared to 2% of

other immigrants and 13% of U.S. natives. These responses suggest that advisors' professional networks serve as an important mechanism through which immigrant students—particularly those from Asian LMIC countries–gain access to industry-facing opportunities during training. Interviews echo this pattern. As one advisor described, *"Companies have been quite good about having [internships], knowing that they can act indirectly as a recruiting pipeline for them."*. Another noted that these links often operate through alumni network, "former students who are now in other places act as an informal alumni network".

The positive relationship between advisor industry ties and internships for Asian LMIC students is particularly salient at non-top-ten universities and outside computer science departments (Appendix Table A11). One interpretation is that in departments or institutions with less formalized links to industry, advisor networks and personal connections play a larger role in facilitating access for these groups of students. This interpretation aligns with qualitative evidence: students at lower-ranked programs tended to rely on advisors' contacts to secure internships, whereas those in elite computer science departments had access to formal partnerships with companies or structured internship programs. As one interviewee explained, at a top-ranked program "almost everyone" undertook industry internships because the department maintained ongoing partnerships with leading companies that returned each year to recruit and fund graduate students. By contrast, in a mid-tier program, he noted that industry internships were uncommon. Together, these patterns indicate that pathways into industry during the PhD differ not only across student groups but also across institutional and disciplinary contexts.

Stylized finding 2: Immigrant PhD students, especially those from Asian LMICs, are more likely than natives or other immigrant groups to engage with industry during their studies. They pursue industry internships at higher rates—particularly in top AI firms—supported by advisor and university networks.

5.2.2 Post-graduation employment patterns

We lastly examine first job placements after the PhD, using an approach that mirrors our earlier analysis on internships. The summary statistics in Table 2 already suggest striking cross-group differences in first job placements. As noted earlier, 70 percent of Asian LMIC students take industry positions immediately after the PhD, compared with 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).

Table 5 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 (Table A12) and post-2016 (Table A13).

[Table 5 about here.]

Importantly, these differences do not reflect lower academic ambition or ability. Survey evidence (Figure A5 shows no significant difference between Asian LMIC and native students in their likelihood of applying for or receiving academic job offers. Instead, the results suggest that immigrant (especially Asian LMIC immigrant) students' training experiences—marked by greater exposure to industry networks during the PhD—channel them toward industry roles upon graduation.

Figure 1b provides a visual summary of these patterns, linking students' country-of-origin groups to their first post-PhD jobs. The diagram underscores the skew toward industry among Asian LMIC immigrants, compared with a more balanced distribution for U.S. natives and other immigrants. This visual representation complements the quantitative results, illustrating how doctoral training channels different student groups into distinctive segments of the AI labor market.

The patterns we've observed so far suggest that industry engagement during the PhD may serve as a structured pathway into post-graduation employment, particularly for Asian LMIC students. We explore the role of internships as one of the primary mechanisms linking doctoral training to placement in elite industry positions.

5.2.3 Internships as a hinge to elite industry employment

Internships appear to act as a key bridge between doctoral training and post-graduation employment. Columns 3 and 6 of Table 5 show a strong positive association between having an internship during the PhD and taking an industry job afterward, including at top AI firms. Interviews reinforce this interpretation. One respondent 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."*

The internship-to-job link is particularly salient for Asian LMIC students. Among those employed at top AI firms, only 39% of Asian 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 A14 shows that this pattern holds across university ranks but is somewhat stronger for students outside computer science departments, again consistent with the idea that internships function as a structured point of entry into industry.

Echoing the findings earlier regarding the advisor's role in securing industry internships, particularly for immigrant students, in our survey, more than 40% of Asian LMIC students indicated that their advisor had a significant influence on career outcomes, compared to 30% of other immigrants and U.S. natives. Appendix Figure A3 also reveals that advisor advice appears to play a much more significant role in select-

ing post-PhD jobs for Asian LMIC students, compared to other groups; and further, existing connections, secured during internships or the PhD program also appear to play a greater role. Advisor influence also emerges clearly in the qualitative material. As one faculty member put it, when asked what most determines whether a student pursues industry or academia, they responded *"the biggest factor, maybe, is the relationship with their advisor."*

Taken together, these descriptive patterns reveal that the pathways through U.S. doctoral programs differ systematically across student groups. While immigrant students as a whole show somewhat greater industry involvement than U.S. natives, the pattern is overwhelmingly concentrated among Asian LMIC students. They are markedly more likely to undertake industry internships, coauthor with industry researchers, and begin their post-PhD careers in top AI firms. In contrast, other immigrant students exhibit outcomes that are closer to those of natives once program, advisor, and productivity factors are held constant. For Asian LMIC students, the PhD thus appears to function as a structured entry point into U.S. industry, supported by advisor and university linkages that connect foreign training systems to the domestic AI labor market.

Stylized finding 3: Immigrant PhD students, especially from Asian LMICs, are more likely to enter industry roles—particularly in top AI firms—after graduation, compared to natives or other immigrant groups. Industry internships serve as a key bridge into these elite firms, a pathway disproportionately used by Asian LMIC students.

6 Discussion

In this paper, we examine how U.S. universities shape the pathways of highly skilled immigrant talent into the U.S. artificial intelligence (AI) private sector. This question is critical, given that immigrant workers account for a disproportionate share of innovation in the U.S., and yet little is known about how they are attracted to the U.S., trained, and placed into these roles. Focusing on top AI PhD programs, we investigate the institutional and social structures that channel immigrant talent into leading U.S. AI firms. In doing so, we ask three core questions. First: How do diaspora faculty facilitate the movement of foreign-trained students into U.S. AI doctoral programs? Second: How do immigrant students' doctoral experiences unfold within the AI training environment? And Third: How do these training trajectories influence transitions into top U.S. AI firms for immigrant students?

Using detailed data on AI PhD students graduated from top U.S. programs, we document three core findings. First, immigrant students, especially those from Asian LMICs, often pair with diaspora advisors. These matches emerge through faculty diaspora networks—built on reputation, prior contact, and shared culture—that bridge talent in Asia to U.S. universities and firms. Second, immigrant PhD students, especially those from Asian LMICs, are more likely than natives or other immigrant groups to engage with industry during their studies. They pursue industry internships at higher rates—particularly in top AI firms—supported by advisor and university networks. Third, immigrant PhD students, especially from

Asian LMICs, are more likely to enter industry roles—particularly in top AI firms—after graduation, compared to natives or other immigrant groups. Industry internships serve as a key bridge into these elite firms, a pathway disproportionately used by Asian LMIC students. These findings highlight how Ph.D. programs and, especially faculty with immigrant backgrounds and institutional structures and networks, act as critical bridges between global scientific talent and the U.S. innovation ecosystem.

Our results contribute to several research streams. First, we add to the migration and organizations literature by shifting focus from the well-documented benefits of hiring skilled immigrants to the upstream process through which such talent enters firms in the first place. While prior research has shown that immigrant hiring improves firm performance (e.g., Stephan and Levin, 2001; Beerli et al., 2021; Brinatti et al., 2023; Glennon et al., 2024; Hunt, 2011; Bernstein et al., 2022), less is known about the institutional pathways that channel immigrant scientists into top private sector roles. Building on work that highlights at a high level the role that U.S. universities play as key channels through which high-skilled immigrants enter the U.S. economy (Bound et al., 2015; Amornsiripanitch et al., 2021), we describe how universities provide a structured pathway from home countries to U.S. firms. We show that diaspora faculty and advisor networks play a central role in this process. In doing so, we uncover a structural process by which the representation of immigrant-origin faculty can shape the long-term composition of the innovation workforce. Our results also extend research on migration by moving beyond aggregate analyses of wage differentials and policy effects to examine the institutional and relational channels through which talent moves. While prior research has emphasized that economic incentives and immigration policies shape who migrates (Grogger and Hanson, 2011; Bound et al., 2021), less is known about how these incentives interact with institutional structures and social networks to guide individual career trajectories. We show that global talent flows are not simply the outcome of individual decisions responding to market signals, but instead emerge where economic opportunities, legal access, and organizational pathways align, highlighting the importance of embedding migration within broader institutional contexts.

Second, our work contributes to the literature on homophily and diaspora networks by demonstrating how relational mechanisms influence the movement of talent across borders. Prior studies have highlighted the role of trust, shared identity, and network-mediated information in shaping collaboration and mobility (Freeman and Huang, 2015; Kerr and Mandorff, 2023; Nanda and Khanna, 2010; Dustmann et al., 2016), but they rarely situate these networks within institutional settings or examine their interaction with immigration regimes. We show that diaspora and conational faculty networks are critical in guiding immigrant students through complex educational and labor market systems, providing referrals, mentoring, and information that help navigate both institutional and legal barriers. In doing so, we reveal how relational structures and social capital are leveraged to translate opportunity into actual migration and employment outcomes.

Third, we contribute to organizational research on pipeline hiring by highlighting how structured recruitment pathways operate in a global context. While prior work has examined how firms rely on es-

tablished educational and professional channels to identify candidates domestically (e.g., Brymer et al., 2024), less attention has been paid to how these pipelines intersect with international mobility. We show that universities act as global talent pipelines, channeling skilled students from home countries into top private-sector positions, and that diaspora faculty and advisor networks amplify this process.

This study has some limitations that merit discussion. First, our study focuses on a narrow, albeit important, setting: immigrant PhD 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: diapora advising relationships, industry internships, and reputational pipelines from sending countries are not unique to AI. On the other hand, however, AI is in many ways an outlier relative to other fields: 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.

That said, the mechanisms we uncover are likely to apply in other fields where immigrants are navigating high-stakes professional environments where the conditions such as global wage gaps, high demand for talent and strong education systems in home countries apply. In disciplines with lower demand for PhDs in industry, or less international student presence, pathways may differ. Our findings are therefore most likely to generalize to STEM fields, especially those undergoing rapid change or where the industry-academia 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 domains.

The patterns we document have important implications for how firms and universities contribute to and benefit from international scientific talent pipelines. For firms, our results highlight the pivotal role that Ph.D. advisors—and in particular, diaspora or conational advisors—play in channeling skilled immigrant labor into the U.S. private sector. These advisors act not just as recruiters of immigrant talent into the U.S. and as their academic mentors, but also as de facto gatekeepers to industry careers, particularly through their ability to facilitate industry internships. Consequently, policies that restrict access to international students or that disrupt the ability of immigrant faculty to advise Ph.D. students or to generate industry relationships are likely to impair firms' access to high-skill talent in cutting-edge fields such as artificial intelligence.

Recent shifts in U.S. immigration policy—including efforts to deport international students and faculty—raise important concerns for the future of the American innovation economy given the results revealed in this paper. Specifically, our findings suggest that U.S. PhD programs, particularly in cutting-edge fields like artificial intelligence, serve as one critical entry point for foreign-born scientists into the local workforce. Constraints on the flow of international students and faculty, therefore, are not only likely to limit access to global talent, but may also disrupt a mechanism linking doctoral education to the innovation

workforce.

Moreover, barriers to international mobility can create second-order effects by constraining the presence of immigrant-origin faculty in U.S. universities. Given the strong conational matching patterns we document, the loss of immigrant advisors could reduce the future enrollment of immigrant Ph.D. students, weakening one of the institutional pipelines that connects global talent to the U.S. innovation economy. Together, these disruptions—whether in student recruitment or faculty advising—may not only shrink the pool of doctoral talent entering U.S. industry, but also sever a key institutional mechanism by which universities channel international scientific capacity into high-value economic activity.

To better understand the magnitude of these potential disruptions, we conduct a set of back-of-the-envelope calculations. Among immigrant PhD graduates in our sample, 65% take an industry job (with 45% taking a job in a top AI company) in their first position post-PhD, compared to 51% of native graduates (25% in top AI jobs). If immigrant and native students are not perfect substitutes-consistent with evidence on skill complementarity and firm-specific hiring channels (Choudhury and Kim, 2019)—then eliminating access to immigrant students could reduce the number of PhD-trained workers entering the innovation sector by 6.5 for every 10 immigrant students excluded. Even if they were replaced one-for-one with native students, the number of industry-bound PhDs would fall from 6.5 to 5.1 (and a drop from 4.5 to 2.5 entering top AI firms).

What about if the number of immigrant faculty in the U.S. was reduced? 53% of immigrant students have an immigrant advisor, compared to 33% of native students. Assuming no alternative advisors exist for these immigrants, and assuming one advisor per student, for every 10 immigrant faculty eliminated from U.S. universities, we would expect a reduction in immigrant students by 5.3 students lost. Given the proportion of those students expected to enter into industry, that would result in a loss of 3.45 students entering industry (2.39 in top AI jobs).

This shortfall matters not only for workforce size but also for innovative output: in Appendix Figure A6, we show that (although the standard errors are large) immigrant Ph.D. graduates in industry produce more patents per year than their native peers, suggesting that restrictions on international student enrollment or barriers to immigrant faculty advising could directly reduce annual firm-level innovation output.

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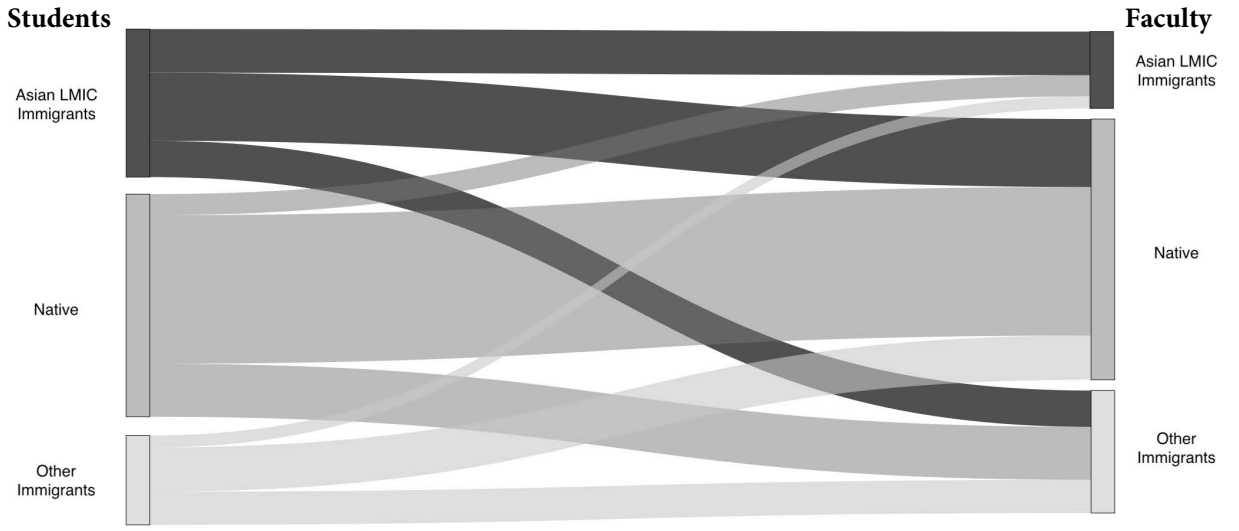
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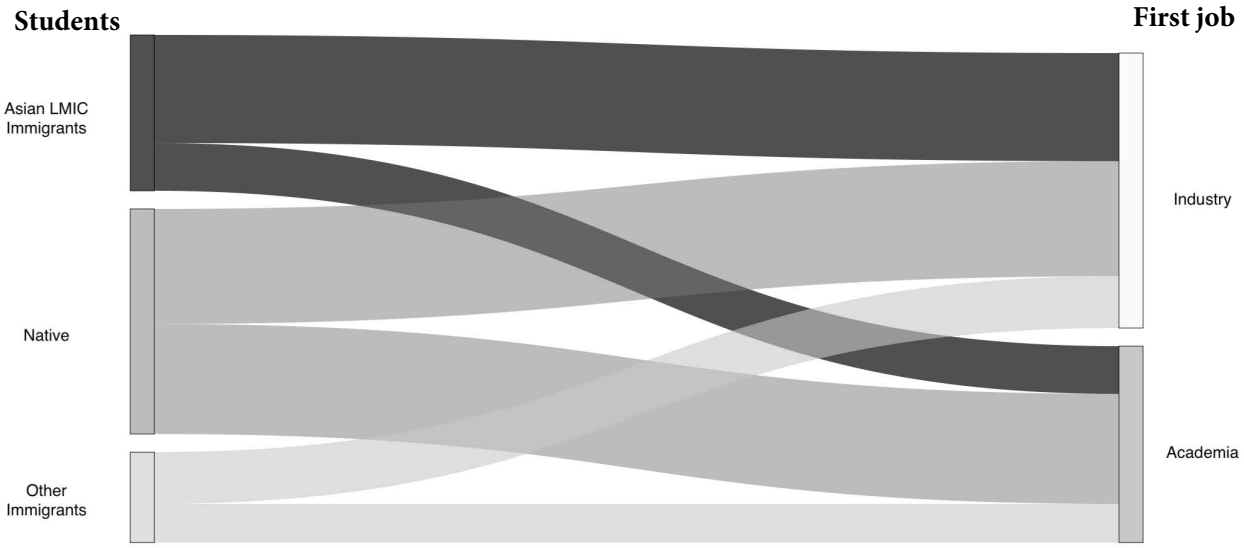
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Figure 1: Student–advisor and student–industry flows.

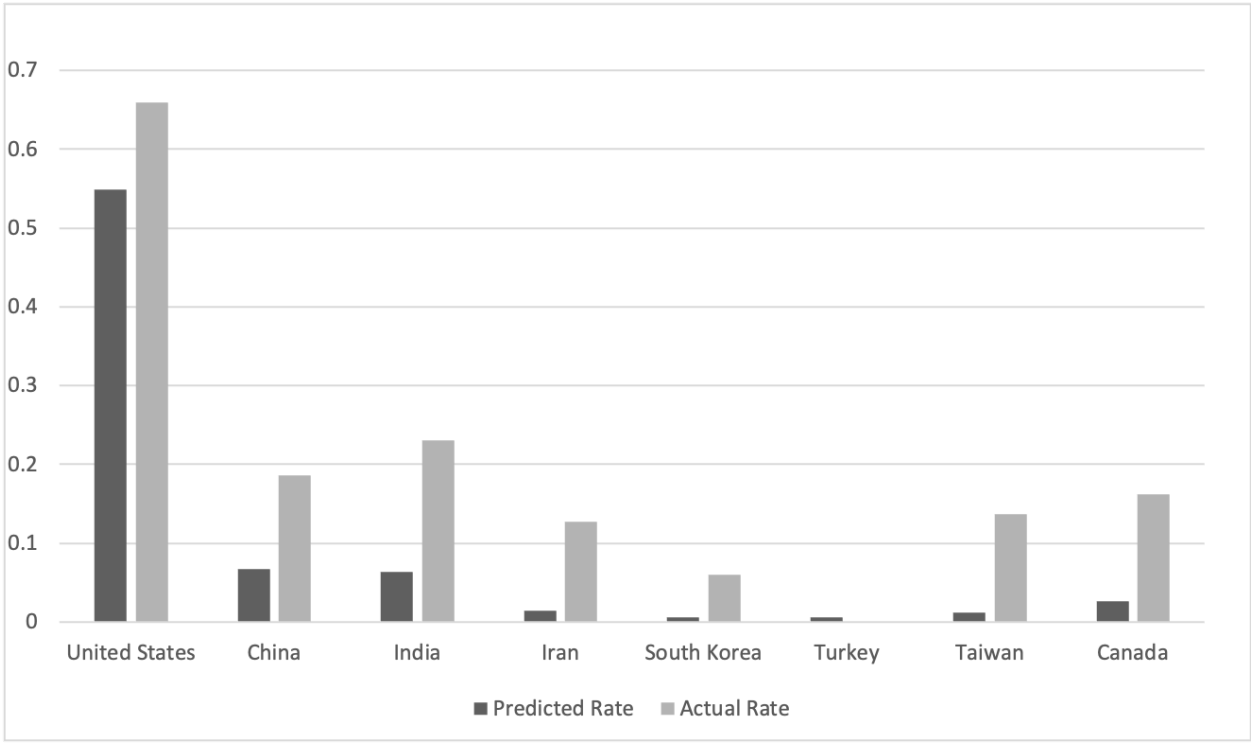


(a) Flows from students' undergraduate countries to advisors' undergraduate countries.



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

Figure 2: Predicted and Actual Rate of Coethnic Matching



Notes: Predicted matching rates assume random assignment of students to advisors, presenting 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 in each of the top eight represented countries.

Table 1: Graduating Institution for Study Sample AI Students

	Nb Students in Sample	Native Student %	Asian LMIC Student %	Other Immigrant Student %
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	0.334
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 (Nb Students in Sample) is the count of sample students in each category. Column 2 (Native Student %) is the percentage of sample students who completed their undergraduate education in the United States. Column 3 (Asian LMIC Student %) 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 Student %) 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 Student	Asian LMIC Student	Other Immigrant Student
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)
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 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. 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 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 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. [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 student 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 student 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 first job post-PhD. Columns 4-6 report the likelihood of having a top AI job as 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.