In Good Company: Coethnic Advisors and Career Paths of Immigrant Ph.D. Students

May 1, 2025

Abstract

In this paper, we examine the role of coethnic advisor-student matching in U.S. Ph.D. programs in attracting, training and guiding immigrant talent into top jobs in Artificial Intelligence (AI). Using comprehensive administrative data on 1,769 AI Ph.D. graduates from top U.S. programs, combined with their advisors' profiles and post-Ph.D. employment outcomes, and complemented by original survey data, we document two new findings. First, immigrant students systematically match with coethnic thesis advisors at markedly higher rates than would be expected by chance. This matching is shaped by reputational spillovers, pre-Ph.D. contact, and preference for shared backgrounds. Second, immigrant students with coethnic advisors are more likely to enter high-quality industry jobs after graduation than their native counterparts. We find suggestive evidence that this is driven by access to industry internships, facilitated by these advisors' unique professional networks. Our findings reveal that universities, through their immigrant-origin faculty, act as critical conduits connecting global scientific talent to the U.S. innovation economy. An important organizational implication of our results is that disruptions to immigration may constrain firm-level access to talent and weaken the academic-to-industry pipeline.

1 Introduction

A growing body of research has investigated the link between hiring immigrants and firm performance (Stephan and Levin, 2001; Beerli et al., 2021; Brinatti et al., 2023; Glennon et al., 2024; Hunt, 2011; Bernstein et al., 2022), largely finding that hiring more immigrants leads to better firm outcomes, particularly around innovation. Consistent with this research, foreign-born workers account for large shares of employees at U.S. firms, particularly in frontier innovation sectors.[1] Among these workers, Ph.D. holders represent a particularly important subset for innovative firms, as they bring both up-to-date knowledge (Zellner, 2003) and embodied tacit knowledge (Agrawal et al., 2006; Zucker et al., 2002) that can be helpful for commercializing inventions. While prior work has examined the firm-level benefits of hiring immigrant Ph.D. scientists, relatively little is known about how these individuals arrive at such firms. In particular, U.S. universities appear to play a central role in this process, serving as a key entry point for many high-skilled immigrants (Bound et al., 2015; Amornsiripanitch et al., 2021), yet the processes by which they recruit and train immigrant talent through Ph.D. programs and connect them to U.S. based innovative firms remain less well understood.

In this paper we explore an understudied mechanism for how universities might attract, train and guide immigrant talent into innovative firms: through coethnic advisors. Whilst many skilled immigrants arrive in the U.S. through universities,[2] these students may face challenges in applying to and navigating foreign Ph.D. programs, such as gaps in information, cultural differences, language barriers, and unfamiliar academic norms. Similarly, departments and faculty may struggle to evaluate and mentor international applicants due to unfamiliarity with grading distributions, institutional reputations, and academic norms, with language and cultural differences potentially complicating the assessment and support process.

Advisor-student matching based on shared backgrounds, or coethnic ties, can mitigate these dual-sided challenges. For instance, an advisor with an Indian background might have more information on the top Indian universities and the standard grade distribution from those universities to help evaluate applicants or current Ph.D. students from India. They could also leverage their networks in India to find out more about or even recruit a given Indian applicant; these kinds of search mechanisms can help to achieve better match quality (Dustmann et al., 2016; Åslund et al., 2014). Beyond facilitating the exchange of information, coethnic advising may be preferred by both students and advisors due to enhanced communication through shared language, or a sense of familiarity, comfort, and trust arising from a shared cultural background. While coethnic ties—through informational benefits, social support, and shared identity—have been shown to influence outcomes in other contexts, we know much less about whether and how they influence advisor-student matching among immigrants. This gap also raises questions about the implications

[1] For example, according to the 2022 Silicon Valley Index, foreign-born workers accounted for 64% of tech workers in Silicon Valley in 2019. See https://jointventure.org/download-the-2022-index last accessed 4.16.25.

[2] This channel is utilized by immigrants at least in part because of institutional features of the U.S. visa system. For instance, while there is a restrictive cap on the number of H-1B visas that can be issued to skilled immigrant workers at private firms, there is no such cap on the number of F-1 student visas, so it is much easier for a skilled immigrant to obtain a student visa than an employment-based visa.

of such matching for the career outcomes of Ph.D. graduates.

Specifically, coethnic student-advisor matching may influence post-Ph.D. career paths of immigrant students. Advisors shape students' exposure to career paths, opportunities, and networks (Azoulay et al., 2017; Roche, 2023; Gaulé and Piacentini, 2018), and coethnic advisors of immigrant students-as immigrant-origin themselves-may differ systematically from their non-immigrant-origin peers in their own professional networks or career paths. These differences could channel immigrant students into distinct sectors, reinforcing patterns of occupational clustering through the training process—similar to how ethnic networks shape the development of specialized skills amongst immigrants in other labor market contexts (Patel and Vella, 2013; Kerr et al., 2021). Understanding whether and how these advising relationships form, and the extent to which they influence occupational sorting, remains a crucial empirical question—especially given the structural constraints faced by immigrant students and faculty in the U.S. and the central role of Ph.D. training in shaping the future innovative workforce.

We characterize the coethnic advisor match of immigrant Ph.D. students and describe its relationship with occupational choice using detailed longitudinal data on 1,769 graduates of U.S. top Ph.D. programs with Artificial Intelligence (AI)-related dissertations collected by the Center for Security and Emerging Technology (CSET) at Georgetown University. AI is an ideal setting for this study due to its potential to transform innovation, the economy, and society; the fact that cutting-edge research occurs in both academia and industry; the high share of foreign-born students; and the strong tendency of U.S.-trained AI Ph.D.s to remain in the country after graduation (95% in our sample), limiting confounding between location choice and occupational choice. The data include, for each student, their dissertation topic, advisor(s), university and department affiliation, and employment records for up to six years post-Ph.D. We infer immigrant status from undergraduate degree location and measure coethnicity using both measures of shared undergraduate country between advisor and student and shared name-based nationality classification (via NamePrism). We link students and advisors to their full publication and patent records using OpenAlex and PatentsView. To complement the administrative data and explore mechanisms behind advisor matching and career outcomes, we also field original surveys of both students and advisors.

Using these unique data, we document two key new findings that advance the literature's understanding of the immigrant pathway into industry. First, we find that immigrant Ph.D. students are significantly more likely to match with coethnic thesis advisors in U.S. institutions than would be expected by chance, and in comparison to their native counterparts. This pattern is particularly pronounced among Asian immigrants and is not explained by differences in advisor quality, productivity, or industry orientation. Survey evidence suggests that preferences for shared background, prior contact, and home-country reputation spillovers play an important role in shaping these matches, with many immigrant students identifying coethnic advisors before arriving in the U.S. These findings point to an endogenous matching process shaped by both information flows and preferences for cultural familiarity.

Second, we show that immigrant Ph.D. students are more likely than their native counterparts to en-

ter high-quality industry jobs after graduation — a pattern shaped, in part, by coethnic advisor matching. Immigrant-origin advisors, particularly those of Asian descent, are more likely to collaborate with industry researchers and to have students with industry internships during their Ph.D.s. These internships, in turn, are strongly predictive of post-Ph.D. industry placement. Survey responses reinforce this mechanism: immigrant students with coethnic advisors are more likely to report receiving industry exposure through their advisor. We find little evidence that these patterns are driven by pre-Ph.D. differences or selection into industry-oriented advisors; rather, it appears that advisor networks shape students' exposure to industry pathways over the course of the Ph.D. Putting these facts together, our results demonstrate that immigrant and immigrant-origin advisors in U.S. universities play an important role in pulling top talent from other parts of the world and in guiding that talent towards U.S. industry.

By bridging literatures on coethnic networks, migration and organizations, and advisor influence, this paper identifies a previously overlooked channel through which high-skilled immigrants are attracted, trained, and placed into top firms in the U.S. private sector: coethnic Ph.D. advising. While prior work has shown that advisor identity can shape students' research agendas and placement outcomes, and separately, that coethnic ties influence entrepreneurship, hiring, and investment, we are among the first to connect these literatures by showing how shared background between immigrant students and advisors drives both advisor matching and downstream occupational sorting. Our findings highlight coethnic advising as a mechanism that not only mitigates challenges before and during graduate training, but also expands access to industry opportunities via advisor networks. In doing so, we illuminate a structural, identity-based process that links immigrant faculty representation to long-term workforce composition and deepens our understanding of how universities channel global talent into high-demand sectors.

These findings also have important organizational and policy implications. Immigrant-origin Ph.D. advisors play a crucial role in guiding international students into U.S. industry, especially in high-demand fields like AI, by facilitating exposure to industry opportunities. For firms, this advisor-student 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. At the same time, as more students, particularly top immigrant talent, pursue industry roles, universities may face growing challenges in staffing academic positions in fast-moving fields.

2 Literature Review

2.1 Coethnic Matching and Advisor Selection

Although immigrant students make up a large share of Ph.D. students in U.S. universities (Bound et al., 2015; Amornsiripanitch et al., 2021),[3] they often face significant challenges in applying to and navigating foreign Ph.D. programs, including information gaps, cultural differences, language barriers, and unfamiliar academic norms. At the same time, departments and faculty may also face significant challenges in evaluating and mentoring international applicants. Faculty may be unfamiliar with grading distributions, institutional reputations, or academic norms in foreign contexts. Language and cultural differences further complicate these challenges, making it harder to assess the potential of international candidates and support their development. One possible way to mitigate such dual-sided information and adjustment frictions could be advisor-student matching based on shared backgrounds.

For immigrant students, coethnic advisors —those who share a similar ethnic, national, or cultural background— could provide critical support throughout the Ph.D. journey, from navigating the application process to receiving mentorship once enrolled. Such advisors may help address information gaps around program expectations, advisor selection, and professional development. Additionally, immigrant students may be more likely to learn about departments with coethnic faculty due to reputational spillovers in their home-country academic networks, making those programs more visible or appealing.

From the department or faculty side, coethnic advisors of immigrants, as immigrant-origin themselves, may possess information advantages about students from similar backgrounds. For example, immigrant-origin advisors can leverage personal information or international networks to obtain more detailed information about applicants or even directly recruit students with shared backgrounds. Such search mechanisms, which bridge ethnic and immigrant networks, can foster a more efficient and informed matching process. Indeed, this is consistent with the literature showing that better match quality emerges when such networks are leveraged for recruitment (Dustmann et al., 2016; Åslund et al., 2014). In general, this aligns with research showing that hiring from the same group or source repeatedly –so-called pipeline hiring– can be beneficial, especially when there are gaps in information or understanding (e.g., Brymer et al. (2024)).

In addition to offering informational advantages, coethnic matching may arise from shared trust, familiarity, and cultural alignment, as well as improved communication due to a common language and background. Advisors and students may feel more at ease with one another because of these shared elements, increasing the likelihood of a match. Previous research has highlighted the impact of shared advisor identity on student success. For instance, Gaulé and Piacentini (2018) show that female students are more likely to pair with female advisors, and this match often leads to higher student productivity and a higher likelihood of pursuing faculty positions.

[3] According to the NSF Survey of Earned Doctorates, in 2022, temporary immigrants received 35% of all doctorates in the U.S. in 2022. See https://cis.org/Report/Immigrants-US-Doctoral-Programs last accessed 4.16.25.

Recent research has shown that people from the same ethnic group often work together in certain industries because they share knowledge and have strong social connections, resulting in observable ethnic occupational clustering. For example, Kerr and Mandorff (2023) finds that immigrant groups with close social ties, like those who tend to marry within their group, exhibit high rates of concentrated entrepreneurship in specific industries. These close-knit networks help them develop skills and provide informal mentorship. Indeed, the importance of coethnic ties has featured 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), international trade (Rauch and Trindade, 2002), location choice (Bauer et al., 2005; Cadena et al., 2017), hiring decisions (Åslund et al., 2014; Kerr and Kerr, 2021), and collaboration networks (Freeman and Huang, 2015). Similar mechanisms may drive the formation of coethnic advising relationships in academia, where bridging information gaps and leveraging trust-based channels can complement—or even substitute for—standard selection processes.

Despite these parallels, the literature has not yet examined whether such dynamics extend to doctoral advising, especially in the context of immigrant students. In particular, the specific role of coethnic advising as a mechanism for identifying, attracting, and supporting immigrant students remains underexplored. This is a meaningful omission given that immigrants play an outsized role in firm performance and innovation (Stephan and Levin, 2001; Beerli et al., 2021; Brinatti et al., 2023; Glennon et al., 2024; Hunt, 2011; Bernstein et al., 2022). Understanding how these advising relationships shape the recruitment and development of immigrant talent is essential, especially in the U.S. scientific workforce and in high-demand fields like AI, where immigrant researchers are central to innovation. This leads to our first research question:

RQ1: To what extent do immigrant Ph.D. students in AI disproportionately match with coethnic advisors?

2.2 Advisor Coethnic Matching and Student Occupational Choice

Coethnic student-advisor matching may not only affect immigrant students' access and mentorship during the Ph.D., but may also shape their long-term career trajectories, and particularly whether they pursue careers in either academia or industry. Prior research has highlighted several factors that shape whether Ph.D. graduates go into industry or academia, including funding opportunities, training experiences, and preferences and ability (Stern, 2004; Agarwal and Ohyama, 2013; Roach and Sauermann, 2010, 2024; Sauermann and Roach, 2012, 2014; Azoulay et al., 2017; Roche, 2023; Gaulé and Piacentini, 2018). And in particular, a growing literature has explored the role of advisors on students' career trajectories. For instance, Azoulay et al. (2017) shows that Ph.D. advisors who engage more in commercial activities can shape their students' long-term commercialization orientations, even when such goals were not the basis for the initial match. Similarly, Roche (2023) finds that students with more entrepreneurial advisors are less likely to pursue academic careers. Gaulé and Piacentini (2018) demonstrate that shared student-advisor gender identity influences female students' productivity and academic career success. These findings suggest that advisor matching can shape student career trajectories even when career decisions are not an explicit part

of the matching process.

In our context, coethnic advisors may exert influence on immigrant students' career trajectories through several channels. First, as immigrant-origin scientists themselves, they may pursue distinct research agendas—such as more applied or commercially oriented topics—which in turn could shape the kinds of projects their students undertake. These research orientations may make students more visible or attractive to industry employers, or shift their own interests toward nonacademic careers. For example, recent research suggests that immigrant scientists exhibit stronger commercialization tendencies, potentially driven by economic constraints or barriers in securing funding within traditional academic routes (Roach et al., 2019). In high-demand fields like AI in the U.S., where much of the cutting-edge work occurs in industry (Ahmed et al., 2023), high-performing immigrants may be particularly well positioned to engage with or transition into private-sector roles (Hunt, 2011; Gaulé and Piacentini, 2013). Indeed, foreign-born doctorate holders tend to have a higher rate of private-sector employment than their native-born counterparts.[4] These patterns suggest that immigrant-origin advisors may shape not only the research topics students pursue, but also the institutional settings in which they are likely to apply those skills.

Second, immigrant-origin advisors may be embedded in distinct social and professional networks, which can shape the opportunities available to their immigrant students. These networks may provide access to internships, job placements, or endorsements that reflect the advisor's own connections and experiences. For example, driven by coethnic clustering itself, the high representation of Asian-origin researchers in the U.S. tech industry[5] may lead Asian-origin advisors to have stronger industry ties. These connections, in turn, could translate into greater exposure to private-sector opportunities for their students. Brymer et al. (2024) show that repeated hiring from the same source—or pipeline hiring—can provide firms with better ex-ante information and stronger post-hire outcomes. Similarly, coethnic advising relationships may act as informal pipelines, channeling immigrant students toward specific career paths.

That said, some immigrant-origin faculty may be more academic oriented or embedded in academic networks as compared to their non-immigrant-origin counterparts. Structural constraints, such as visa restrictions or limited access to research funding, might make academia a more attractive or stable outcome for first-generation immigrant faculty. Amuedo-Dorantes and Furtado (2019) find that post-2004 restrictions on the H-1B visa increased the likelihood that foreign-born graduates in the U.S. stayed in academia. And Ganguli and Gaulé (2019) find that foreign STEM students view tenure-track positions more favorably than U.S. students, suggesting a possible preference for academic careers among immigrant-origin scientists.

Regardless of whether advisors are oriented towards industry or academia, these distinctions underscore the potential importance of advisor coethnicity in shaping immigrant students' career outcomes. Immigrant-origin faculty may, for example, facilitate access to internships or professional opportunities

[4] See https://ncses.nsf.gov/pubs/nsf21336 last accessed 4.15.25

[5] According to Joint Venture Silicon Valley's index, Asians and Asian-Americans comprise more than 56 percent of Silicon Valley's tech industry. At Facebook, Google, and Apple, Asian employees either outnumber other ethnic groups or are the second-largest group behind white employees.

in the private sector by drawing on their own networks and experiences. In fields like AI, where industry plays a central role in advancing the research frontier and where foreign-born scientists are heavily represented, such support could be particularly consequential. Conversely, immigrant-origin advisors who are more academically oriented—perhaps due to structural constraints or personal preferences—may steer students toward academic opportunities through their own networks and mentorship. In this way, coethnic advising relationships could act as a sorting mechanism, channeling immigrant students into specific occupational pathways shaped by advisors' orientations, experiences, and networks. This leads us to our second research question:

RQ2: How does coethnic advisor matching influence the career outcomes of immigrant AI Ph.D. students—particularly their likelihood of entering industry?

3 Setting, Data, Measures and Descriptive Statistics

3.1 Sample of Artificial Intelligence Ph.D. Graduates

To study these questions, we use a sample of Ph.D. students who graduated between 2014 and 2018. These individuals are determined based on (1) graduating from the twenty highest-ranked U.S. Ph.D.-granting institutions in Artificial Intelligence (AI)-related fields between 2014 and 2018 inclusive, (2) having publicly available employment and educational histories, and (3) having written an AI-related dissertation, as collected by the Center for Security and Emerging Technology (CSET).[6] Whether a dissertation was AI-related or not was determined by CSET using a keyword approach on all dissertations that could be found in ProQuest.[7] Importantly, these graduates are selected based on whether their dissertation is related to AI, not by whether they're in a computer science department. Therefore, as shown in Table 1, these graduates are coming from a wide range of departments.

CSET then collected comprehensive education (undergraduate and graduate degrees, including information on institution, department, advisor name(s) and date of graduation) and career (employer, job position, and dates of employment) details of each graduate for the full period prior to their Ph.D., during their Ph.D. and for up to six years after completion of their Ph.D.[8] For our primary analysis, we leverage information on the first job post-Ph.D. for each sample graduate, because this is the choice most likely to be shaped by the advisor and Ph.D. experience.

We supplement any missing data with manual internet searches, and we also added several new fields

[6]Full educational and career trajectories could not be obtained for every scientist with an AI-related dissertation. Table A1 in the online appendices provides a comparison of the sample used in the analysis—which is restricted to those Ph.D. graduates for whom career information could be obtained—and the full sample of graduates including those for whom undergraduate institution and post-Ph.D. graduation employment history was not obtained.

[7]A comprehensive query of full text of all Ph.D. dissertations was used to identify AI related theses. Some example search phrases include "information retrieval", "autonomous vehicles" and "random forest". The resulting theses were then filtered for false-positive results (dissertations using keywords in a context unrelated to AI and machine learning).

[8]Data collection took place in 2020, which means that the data on more recent graduates is truncated.

to the CSET data. Employers are manually categorized into two main groups: academia and industry.[9] Industry employers are further categorized as top employers, and as either startups or multinational corporations (MNCs). We proxy for top industry employers by identifying the so-called "FAANG" companies (Facebook, Amazon, Apple, Netflix and Google). These are among the best performing technology companies in the world and account for almost ten percent of the U.S. stock market's total capitalization.[10]

As we do not have access to the country of birth or visa status of the sample graduates, we use a proxy for immigration status. Our primary indicator of whether or not a graduate is an immigrant is 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 are immigrant students (Bound et al., 2015). To conduct some of our analysis we also rely on information on the name nationality of each sample graduate, using the NamePrism algorithm which assigns the most probable name nationality using the first and last name of each individual. For much of our analysis we also separate immigrants into two groups: Asian and non-Asian immigrants, classifying Asian immigrants as those who completed their undergraduate education in (or classify as having a name nationality originating from) China, India, Taiwan, Cambodia, Japan, South Korea, Malaysia, Pakistan, Thailand or Vietnam.

Our main sample consists of 1,769 AI Ph.D. graduates. As shown in Table 1, just over half of the Ph.D. graduates in our sample are immigrants, as defined using the undergraduate degree definition, with Chinese immigrants making up the largest portion at 20% of the full sample and Indian immigrants making up the second largest portion at 8% of the full sample. Immigrants from high-income countries (defined as OECD countries) comprise 7% of the full sample.[11] In Table 1, we also provide details on the set of institutions and departments that the individuals in our sample graduated from.[12] Over 40% of the sample graduated from engineering departments, and 30% graduated from mathematics and computer science departments. Lastly, Table 1 provides information on the ten most common post-graduate employers of sample individuals. Among the ten most common employers are five firms—Google, Facebook, Microsoft, Amazon, and Apple—–which all have an especially high share of immigrant hires (63-78%, which exceeds the average immigrant proportion in the sample of 52%). Notably, with the exception of Microsoft, these are also all FAANG firms.

[Table 1 about here.]

A similar descriptive table for the advisors of these Ph.D. graduates can be found in Table A3.

[9] 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.

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

[11] An overview of the undergraduate institution countries represented in our sample can be found in Appendix Table A2.

[12] Note that we standardize department names across our sample.

3.2 Advisor Coethnicity

We generate measures of advisor coethnicity in a few different ways. First, mirroring our immigrant classification approach for Ph.D. graduates, we identify whether or not each advisor completed their undergraduate degree outside of the U.S. as a proxy for immigrant status. We obtained this information using department websites and online resumes. Second, we classify the name nationality of each advisor in the sample, again using the NamePrism algorithm and the first and last name of each advisor. Thus, for each sample Ph.D. graduate, we can determine whether at least one of their advisors completed their undergraduate education in the same country as their own undergraduate degree and whether at least one of their advisors shares the same name nationality.[13] Finally, we generate an Asian-specific dummy variable for each measure that takes the value of one for a given Ph.D. graduate if at least one of their advisors completed their undergraduate education in an Asian country or if the advisor had an Asian name nationality designation.

Our preferred measure of coethnicity is shared name nationality.[14] This measure offers three key advantages. First, we might expect that the drivers of coethnic matching would extend to second- and third-generation immigrant faculty, who would otherwise be difficult to identify using conventional indicators such as birthplace or parent's birthplace (data that we do not have access to), or our measure of undergraduate education location. Indeed, Online Appendix Table A5 and Figure A1 —- described in more detail in later sections —- support this view. Second, this approach allows us to compare coethnic matching in the immigrant student group relative to coethnic matching in the native student group. This comparison would not be tractable if we only considered undergraduate location data, as all individuals classified as 'native' would be defined the same way, whereas there is variation within the immigrant group. Third, one of the challenges we face is the large number of advisors in the sample with U.S. undergraduate degrees, which gives different scales across immigrant and native students if advisor undergraduate location is used the main coethnicity measure. The name nationality approach overcomes this challenge by allowing us to further disaggregate the advisors who completed their undergraduate degrees in the U.S. into distinct groups, enabling us to analyze coethnic matching among both natives and immigrants.

3.3 Publication and Patent Data

Each Ph.D. graduate and their Ph.D. advisor(s) in our sample are matched to their full publication history using the OpenAlex API. One of the main challenges associated with using publication databases is the common name problem. Fortunately, OpenAlex generates scientist identifiers and assigns publications (including conference proceedings and preprints) to each scientist in the database based on topic, collab-

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

[14] Note that several name-based coethnicity measures have been used in the literature on coethnic ties. Freeman and Huang (2015); Kerr and Lincoln (2010); Kerr (2008), all use measures of name ethnicity. The name nationality algorithm that we use in our primary measure has the advantage that it generates narrower name nationalities than traditional name ethnicity identifiers. For example, the NamePrism algorithm designates first and last names as originating from: "EastAsian,Japan" or "Nordic,Scandinavian,Sweden".

oration patterns and institution. We identify and extract publications for each sample graduate, refining matches by restricting them to known affiliated institutions within a five-year window.[15] For the advisors, a similar procedure is carried out, searching OpenAlex using advisor name and institution, refining matches through a manual process. We run a very similar procedure to collect patent data for each Ph.D. graduate in the sample using the PatentsView API.

For each sample graduate, we use data on their full set of publications each year to generate counts of publications authored before they start their Ph.D. and during their Ph.D. For each advisor, we count publications in the five-year window prior to the focal graduate's Ph.D. start year to avoid capturing any effects from the student themselves on the advisor. In addition to publication counts, we generate measures on the coauthoring patterns of sample graduates and their Ph.D. advisors. Namely, we generate counts of industry collaborators by using authorship information from OpenAlex, extracting and counting coauthors with affiliation type that OpenAlex labels as "industry".

We also generate measures that indicate the topic orientation of pre-graduation (i.e. Ph.D) publications of each sample graduate. We do so by first extracting the tagged concepts[16] used in a given graduate's Ph.D. period publications and then generating a measure of the "industry orientation" of each concept used. Our primary measure of "industry orientation" of a concept is defined as the ratio of U.S.-based publications using that concept authored by industry researchers to those authored by academic researchers, measured in the graduate's year of graduation. We then average this measure over all concepts used in pre-graduation publications whereby a higher number can be interpreted to mean that the graduate tends to employ concepts used relatively more frequently in industry as compared to academia.

3.4 Survey and Interview Data

Finally, to explore the mechanisms driving our main results we conducted surveys of all sample graduates and their Ph.D. advisors, respectively. Out of our sample of 1,769 Ph.D. graduates and 1,472 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.[17]

The survey of Ph.D. graduates 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.[18] The survey of advisors asked questions around Ph.D. student selection (Q1) and why they might have ended up going into industry or academia (Q2-4), as well as questions around how many students they've advised and where they are originally from. Both graduates and advisors were asked whether they'd be willing to interview with us. We conducted

[15] To resolve outstanding issues related to multiple OpenAlex identifiers with the same name and affiliation we then also exclude author identifiers who never publish in computer science and use advisor and department data to identify the best match(es).

[16] Each work in OpenAlex is tagged with multiple concepts, based on the title, abstract, and the title of its host venue using an automated classifier.

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

[18] 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.

interviews with five individuals between February 26 and March 21, 2025 over Zoom. All survey tools can be found in Appendix B.

3.5 Descriptive Statistics

Table 2 shows raw differences between native and immigrant Ph.D. graduates in our sample across several characteristics. While there is no statistical difference in graduation year, there are significant statistical differences across every other measured characteristic. For instance, a comparison of pre-Ph.D. productivity measures (publications counts) for the two groups shows that immigrant graduates appear to be much more productive prior to their Ph.D. graduation. They are also much less likely to do their Ph.D. at a top five ranked university than natives. Immigrant Ph.D. graduates are more likely to have an immigrant Ph.D. advisor than native graduates (53% versus 33% of natives), and, on average, their advisors seem to have more industry collaborative publications before they begin their Ph.D.

Importantly, more than 90% of Ph.D. graduates in the sample continue to work in the U.S. following graduation, regardless of whether they are immigrants or not. These numbers are broadly consistent with prior work measuring stay rates of immigrant Ph.D. graduates. For example, Finn (2010) finds that 89% and 79% of Ph.D. holders in STEM fields from China and India remain in the U.S. five years after receiving their Ph.D, respectively. Lastly, we can see salient differences between their first job placement: immigrant Ph.D. graduates are much more likely to take an industry job in their first job post-graduation while natives are more likely to take an academic job, a baseline difference to which we will return in Section 4.2.

[Table 2 about here.]

4 Analysis and Results

We investigate our two primary research questions in turn. First, we examine whether immigrant Ph.D. graduates in our sample are more likely to match with coethnic advisors, and what mechanisms drive any observed matching. Second, we assess whether such matches influence the students' career paths, and examine the channels through which any influence operates.

4.1 Advisor Coethnic Matching (RQ1)

In this section, we address our first research question: To what extent do immigrant Ph.D. students in AI disproportionately match with coethnic advisors?

4.1.1 Descriptive Evidence

We begin by providing graphical evidence that students are more likely to match with advisors who share similar backgrounds by comparing the predicted and actual rates of student-advisor matching by

country. To calculate the predicted matching rate, we assume random assignment of students to advisors using the proportion of advisors across our whole sample who obtained their undergraduate degree from each country. For example, if 50% of advisors earned their undergraduate degree in China, then the predicted probability of any student (including Chinese students) matching with a China-educated advisor is 0.5.[19] Next, we compute the actual matching rate, which represents the proportion of students from each country who have an advisor who also completed their undergraduate degree in the same country. Figure 1 plots the predicted and actual match rates for the top eight countries of undergraduate location in our sample. It is immediately apparent even in this raw data that student-advisor coethnic matching occurs at significantly higher rates than expected under random assignment.[20]

[Figure 1 about here.]

4.1.2 Regression Analysis

To ensure that the observed coethnic advisor-student matching is not driven by spurious correlations, we estimate a series of regression models controlling for a rich set of student, advisor, institutional, and disciplinary characteristics. Specifically, we estimate:

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

where Y_i indicates the type of advisor sample graduate i had during their Ph.D., which will vary across specifications. $Immig_i$ denotes an indicator variable that switches to one if graduate i received their undergraduate degree from a non-U.S. institution (our proxy for immigrants). $prePh.Dpubs_i$ is a count of the number of publications authored by graduate i in the years prior to their Ph.D. start year, which allows us to account at least in part for ability. $preIndustryJob_i$ is an indicator for whether or not individual i had an industry job prior to their Ph.D. $advisorindustrypubs_i$ is a count of the number of industry coauthored publications of the advisor (in cases with more than one advisor this value is averaged) in the five years prior to the Ph.D. start year and is included to rule out the possibility that industry-orientation, rather than coethnicity, is driving our results. $advisorhindex_i$ is the advisor's h-index, which accounts for advisor quality or reputation in case, for example, immigrant advisors are of higher quality and that it driving our results. $\delta_{gradyear}$ stands for a full set of graduation calendar year indicator variables to account for the fact that the university environments may vary over time. $\gamma_{institution}$ corresponds to institution fixed effects, to account for whether particular institutions have different kinds of faculty or students, and σ_{dept} corresponds to de-

[19] Note that this does not include the entire universe of potential advisors – rather it only includes sample graduates' 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] We replicate this process for coethnic advisor matching based on name nationality in Figure A1.

partment fixed effects, to control for different kinds of faculty or students across fields (e.g., biology vs. computer science). Standard errors are clustered at the level of the Ph.D. advisor.

Results are presented in Table 3. Even columns include the full host of controls, while odd columns only include fixed effects. In each set of specifications, the inclusion of the full set of controls slightly reduces the size of the coefficient of interest, but the relationship remains strong and statistically robust. Each set of two columns correspond to a particular type of advisor that the focal student matched to.

Columns 1 and 2 show that immigrant students are 13-15% more likely than native students to have at least one immigrant advisor, even when compared within the same institution, department, and graduation cohort. We next examine advisor matching amongst Asian students in our sample, who represent a large proportion of our sample. Columns 3-6 reveal that students from Asia are significantly more likely to be matched with Asian advisors.[21] Further, while the average rate of shared country of origin matching within the immigrant sample is high (15%), reinforcing the idea that shared country of origin influences advisor pairing, we find relatively stronger same-country matching for Asian immigrant students in columns 7 and 8.[22]

[Table 3 about here.]

As discussed earlier, our preferred specification uses name nationality to identify coethnic matches and includes fixed effects for name nationality groups. This approach allows us to isolate the within-name-nationality-group variation, exploring whether immigrant students are more likely to be matched with coethnic advisors than native students. For example, we estimate the difference in the probability of matching with a South Asian–name advisor between two students with South Asian name nationality——one who completed their undergraduate degree in the U.S. and one who did not——controlling for institution, field, graduation year, and both student and advisor characteristics. Figure 2 (associated regression table provided in Appendix Table A5) shows the results: controlling for advisor, student and institution level features, and controlling for name nationality, immigrant students are about 7.5% more likely to match with a coethnic advisor.

[Figure 2 about here.]

We present several robustness and alternative tests of the coethnic student advisor match in the online appendices. In Appendix Table A5 columns 3 and 4, we test whether the matching is driven by second- or third-generation immigrant advisors—as proxied by those who share a name nationality with the student but completed their undergraduate education in the U.S. To do so, we generate a dummy variable that takes the value of one if the advisor shares the student's name nationality but did not study in the same

[21] We focus on Asian vs non-Asian immigrants as the primary dimension of origin country heterogeneity for two main reasons: (1) students from Asia make up the largest proportion of immigrants (35% of the entire sample), and represent a particularly high proportion of the innovative workforce in the U.S. in AI, and (2) students from Asia are particularly culturally (and institutionally) distant from the U.S.

[22] In Appendix Table A4 we exclude non-science and engineering students who may have different selection criteria for Ph.D. programs or advisors. Results remain very similar.

country. Columns 3 and 4 of that table indicate that coethnic matching appears to be even stronger with second- or third- generation advisors. We speculate that the larger coefficient size is a result of the fact that there are not many first-generation immigrant faculty at top 20 universities (as shown in Table A3). We also drop students and advisors with CelticEnglish name nationality designation as they are overrepresented amongst native faculty in columns 7 and 8. Our results remain robust.

In Appendix Table A6, we consider several alternative explanations that could be driving the observed coethnic matching. In order to assess whether the Asian coethnic matching we observe is simply because of more Asian faculty at the universities where Asian students chose to attend, we include a control variable for the number of Asian faculty in the university more broadly (data gathered from the IPEDS NCES database) in the Ph.D. start year (or closest year in which data was available) in columns 2 and 4. Next, in columns 5 and 6, we test whether Chinese or Indian students drive our coethnic name nationality matching dynamics by excluding those who completed their undergraduate education in China and India, respectively. Although still significant, the coefficient on the Asian immigrant indicator variable declines slightly in both cases, implying that these groups of students are playing a significant role in our observed effects. Finally, we consider whether we are picking up a spurious correlation: namely that Asian students are just matching with Asian faculty for reasons other than coethnicity. We generate new variables that equal one if the focal student has at least one advisor with an Asian undergraduate degree or an Asian name nationality, but from a different Asian country than the student's home country in columns 7 and 8. Reassuringly, we fail to find any higher rates of immigrant matching in these groups.

4.1.3 Mechanisms of Matching: Survey and Interview Evidence

To understand why immigrant students disproportionately match with coethnic advisors, we turn to our survey and interview data.

First, we find no evidence that immigrant students prioritize advisor industry or academic ties more than native students when selecting advisors, as can be seen in Figure 3. Nor do immigrant students place more emphasis on mutual connections or alignment with research interests.

[Figure 3 about here.]

However, immigrant students were slightly more likely to select "Advisor's reputation in the field" as an important factor in advisor selection. Importantly, this appears to reflect not just general academic prominence, but country-specific visibility shaped by coethnic networks. In follow-up interviews and open-ended responses, many respondents emphasized how academic mentors in their home countries—often Ph.D. graduates of U.S. institutions themselves—highlighted the reputations of particular coethnic advisors abroad. Because coethnic faculty are more likely to have trained students or collaborated with researchers who subsequently returned to the home country, their names are more likely to be familiar within domestic academic circles. 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 Ph.D. graduates from reputed U.S. institutions"*, describing how prior generational ties between coethnic faculty and home-country institutions may create reputational pipelines. Similarly, one interviewee noted that their mentor, a professor who had obtained their Ph.D. in the U.S., had helped them to identify which Ph.D. programs to apply to based on their familiarity with different departments and faculty. Indeed, the program they ended up attending was the same program as their mentor's. These dynamics make coethnic advisors especially visible and appealing to prospective students from the same country.

Prior contact also appears to play a significant role in advisor selection, particularly among coethnic pairs. Survey responses suggest that immigrant students—especially those with immigrant advisors—are more likely to have chosen their advisor prior to arriving in the U.S. While confidence intervals are wide, 56% of immigrant graduates with an immigrant advisor reported selecting their advisor before arriving in the U.S., compared to 44% of other immigrant and native respondents (Appendix Figure A2). Similarly, nearly 60% of immigrant advisors who supervised immigrants students cited prior exposure to the student as a top three selection criteria—compared to just 35% of other advisors. This may reflect an increased likelihood of interaction—immigrant-origin faculty are more likely to visit their countries of origin for recruiting, conferences, or personal reasons. These visits create opportunities for in-person meetings that can catalyze future advising relationships. Interviews and survey responses recounted brief but meaningful meetings-sometimes just a single campus visit-that seeded long-term advising relationships. For example, one respondent noted in an open-ended question that their advisor visited their home city just once on a business trip, but that meeting was enough to establish a connection.

Finally, immigrant graduates disproportionately selected "shared cultural background" as particularly important when selecting their Ph.D. advisor. Hence, part of the coethnic matching appears to be driven by a preference for having a shared background by both students and advisors. One advisor wrote, in explaining why they like to work with students with a shared background, that: *"There is a somewhat shared set of issues and concerns and language framework."*. Having a shared background can also reduce information asymmetries in the Ph.D. admissions process. It can be difficult to evaluate Ph.D. students ex-ante, particularly in departments that expect them to begin research immediately, and admitting a student with the same background can help to mitigate that challenge. As one interviewee put it: *"International professors who are familiar with those international schools often will also hire from places where they have that deep knowledge."*

To summarize, coethnic advisor matching is prevalent among immigrants and appears to be driven by: (1) reputational spillovers in home-country academic networks, (2) pre-program contact, and (3) a preference for shared background amongst students and advisors alike.

The high prevalence of coethnic advisor matching among immigrants in our sample raises important questions about its consequences. Prior research has shown that advisors play a crucial role in shaping the career trajectories of their students—not just through mentorship, but also by providing access to professional networks and career opportunities. Coethnic advisors of immigrants may not only attract talented

immigrants to U.S. Ph.D. programs but also influence their career trajectories in distinct ways, given their potentially different industry connections, mentorship styles, or institutional access. Therefore, we now turn to our second research question: How does coethnic advisor matching influence the career outcomes of immigrant AI Ph.D. students—particularly their likelihood of entering industry?

4.2 Immigrant Career Outcomes (RQ2)

4.2.1 Immigrant Ph.D. Graduates and Industry Career Paths

We begin by building on a fact that we have already established. Specifically, the descriptive statistics (Table 2) showed that immigrant graduates are more likely than native students to enter into industry following their Ph.D. As we did when establishing coethnic matching, we first turn to regression analysis to ensure this relationship is not driven by a spurious correlation. Specifically, we run the following regression:

$$Y_i = \beta_0 + \beta_1 Immig_i + \beta_2 prePhDpubs_i + \beta_3 PhDpubs_i + \beta_4 preIndustryJob_i + \delta_{gradyear} + \gamma_{institution} + \sigma_{dept} \tag{2}$$

where Y_i is the outcome measure for person i which will vary across specifications but will indicate occupational placement of some kind. $Immig_i$ denotes an indicator variable that switches to one if graduate i received their undergraduate degree from a non-U.S. institution (our proxy for immigrant). To account for ability, we include two publication count variables. $prePhDpubs_i$ is a count of the number of publications authored by graduate i in the years prior to their Ph.D. start year, and $PhDpubs_i$ is a count of the number of publications authored by the focal graduate in the five years prior to Ph.D. graduation (to represent publications produced during the Ph.D). $preIndustryJob$ is an indicator for whether or not graduate i had an industry job prior to the Ph.D, to account for any pre-Ph.D. preferences or aptitude for industry jobs. $\delta_{gradyear}$ stands for a full set of graduation calendar year indicator variables to account for the fact that the research and labor market environments may vary over time. $\gamma_{institution}$ correspond to institution fixed effects, to account for whether particular institutions tend to "feed" into industry jobs, and σ_{dept} corresponds to department fixed effects, to control for different propensities to enter industry across fields (e.g., biology vs. computer science). Standard errors are clustered at the level of the Ph.D. advisor.

Table 4 presents the regression results. Column 1 indicates that immigrant graduates are 11% more likely than non-immigrants to enter industry after graduating from their Ph.D. program, even after accounting for graduation year, department, institution, pre-Ph.D. publications, pre-graduation industry employment, and Ph.D-era publications. In column 2, we show that this effect is primarily driven by Asian immigrants, who exhibit a significantly higher propensity to enter industry relative to other immigrant groups.

[Table 4 about here.]

We provide additional robustness and heterogeneity analysis on the result that immigrant Ph.D. graduates are more likely to go into industry in the Appendix. With respect to heterogeneity, we find that these immigrant graduates are taking high-quality industry jobs: they are particularly likely to occupy FAANG jobs (Appendix Table A7, Columns 1-4). In fact, the higher propensity of immigrant graduates to go into industry is accounted for by FAANG jobs; they are no more likely to go into non-FAANG jobs than native graduates, and jobs in MNCs (as opposed to startups).[23] One possible explanation for this result might be that FAANG companies are among the most active in sponsoring H-1B and green card visas, potentially making them especially attractive and viable employers for international PhDs.

The results do not appear to be driven by those who left the U.S. after graduation (Table A7 Column 5), or by a preference for/against temporary jobs like post-doc positions (Table A7 Column 6), nor is the effect changing significantly over our sample time period (Table A7 Column 7). The effects appear to persist after the first job (Table A7 Column 8), demonstrating that the first job represents a path dependency that continues for up to six years following the Ph.D. The effects also appear to be driven mostly by graduates coming out of computer science and engineering departments (with little difference by Ph.D. institution rank) who might be particularly well positioned to occupy top AI innovation jobs (Appendix Table A8).

There are many plausible reasons as to why immigrant Ph.D. graduates might be more likely to go into industry than their native counterparts. For instance, native graduates might have an advantage in teaching and public speaking, making academia more appealing to them. Another possible explanation is that visa restrictions create significant hurdles for immigrants pursuing academic careers, particularly in the U.S. Many Ph.D.s first work as post-docs before securing a tenure-track position, but post-docs offer limited work authorization options. The common H-1B skilled employment visa in the U.S., used in private-sector jobs, requires employer sponsorship, making it impractical for short-term post-doc roles. Instead, immigrants in these post-doc roles often rely on OPT (Optional Practical Training), which lasts up to three years for STEM graduates but often expires before it's possible to secure a tenure-track job. Even transitioning to the private sector following a post-doc position presents challenges if an OPT visa expires before securing an employee-sponsored H-1B visa. These institutional challenges might make academia a riskier path for immigrant graduates who do not immediately secure a tenure-track position. Further, immigrants may also have different preferences or have different talents and skillsets, leading them along a different career path.

At the same time, career trajectories are not likely to be shaped by structural barriers or preferences alone. As highlighted by prior literature, mentorship and professional networks also play a crucial role. Therefore, we next highlight the central role that advisors—particularly those of immigrant origin, whose shared background often facilitates coethnic matching with immigrant students—play in attracting, training, and channeling immigrant talent into U.S. firms.

[23] This is consistent with work from Roach and Skrentny (2019) who document that immigrants are unlikely to work for startup companies owing to visa constraints.

4.2.2 Coethnic Advisor Influence

To assess the role of advisors, and specifically coethnic advisors, in shaping career outcomes, we add an interaction term in equation 2 between whether the focal graduate is an immigrant and whether at least one of their Ph.D. advisors is coethnic. Results are presented in column 3 of Table 4. The positive coefficient on that interaction term indicates that the higher likelihood of industry placement among immigrant AI Ph.D. graduates is particularly pronounced for those with coethnic advisors.

In column 4 we introduce an indicator for Asian advisor name nationality to distinguish the effects of coethnic advising from advisor identity more broadly. With this control, the coethnic advising coefficient loses statistical significance, indicating that industry placement amongst immigrant graduates is (partly) driven by having an Asian origin advisor. These findings highlight that immigrant students—especially those with coethnic or Asian origin advisors—are significantly more likely to pursue careers in industry, highlighting the role of advisor background in shaping occupational outcomes.

4.3 Mechanisms of Advisor Influence

Taken together, these findings suggest that coethnic advisors play a meaningful role in steering immigrant students toward industry careers. But how, exactly, does this influence unfold? In this section, we explore the mechanisms underlying this relationship.

4.3.1 Ruling Out Selection

We begin by considering whether our results are driven by selection effects—namely, whether immigrant students with coethnic advisors are already predisposed to pursue careers in industry, or whether immigrant-origin advisors are more likely to select students who are oriented toward industry careers.

First, we consider whether immigrant students with coethnic advisors had a stronger preference for industry prior to starting their Ph.D. In Table 3, we included controls for student pre-Ph.D. industry employment, and our coethnic matching results remain robust to the inclusion of that variable. Likewise, Table 4 shows that the positive relationship between coethnic advising and industry outcomes persists even after accounting for prior industry experience.

Second, survey responses do not provide strong support for a selection-based explanation. When asked about their career preferences at the beginning of their Ph.D, immigrant graduates, and particularly those with immigrant advisors, were no more likely to indicate a stronger preference for industry careers than native students or immigrant students with native advisors (Figure A3).

Third, we examine whether immigrant students intentionally selected advisors based on perceived industry connections. Table 3 includes a control for advisor industry publications prior to the student's Ph.D. start, and the results remain robust. Likewise, survey results given in Figure 1 show that immigrant students are no more likely than their native counterparts to report "industry collaborations" as a reason for

advisor choice.

Finally, we analyze whether differences in job application behavior or outcomes may explain observed industry placement. If selection were the primary driver, we might expect immigrant students—especially those with coethnic advisors—to apply more to industry jobs or receive fewer academic offers. Figure A4 demonstrates that immigrants, including those with immigrant advisors, are not significantly less likely to report applying for or receiving academic job compared to other groups. This implies that their eventual decision to enter industry is not likely to be merely a consequence of fewer academic opportunities.

Taken together, these findings indicate that while selection effects may play some role, they do not fully explain the observed relationship between coethnic advising and industry placement for immigrant students.

4.3.2 Role of Internships

In contrast to the selection story, one of the clearest channels through which coethnic advisors appear to influence the career trajectories of immigrant students appears to be via facilitating industry internships. Our survey responses show that immigrant students with immigrant advisors were significantly more likely to answer that their Ph.D. advisor facilitated an industry internship than natives (Figure 4).[24]

[Figure 4 about here.]

These results are corroborated by regression estimates in Table 5, column 1, which shows that immigrant students with coethnic advisors are significantly more likely to participate in industry internships. In contrast, there is no such difference in the likelihood of immigrant students with coethnic advisors to have industry coauthors on their Ph.D. research (column 2) or engage in more industry-oriented research (column 3).

[Table 5 about here.]

Moreover, when we include an indicator for internship participation ("During-Ph.D. Industry Employment") in equation 2 (Table 6 column 2), the previously significant predictive power of the coefficients on both "Immigrant" and "Immigrant $\times$ Coethnic Advisor" disappears. In contrast, the inclusion of explanatory variables capturing whether the focal graduate had a pre-Ph.D. industry job (all columns), had during-Ph.D. publications with industry coauthors (column 3), or engaged in industry-oriented research during their Ph.D. (column 4) does not cause both coefficients to lose predictive power. These results suggest that advisor-facilitated internships are a key mechanism through which immigrant students become more likely to sort into careers in industry.

[Table 6 about here.]

[24] Further, survey responses indicate that advisors played an important role in a career goals shift during the course of their Ph.D. experience, particularly for immigrant graduates: 53% of immigrant respondents reported that their advisor had a moderate or strong influence on their post-Ph.D. career choice, compared to 48% of native respondents.

Interview responses further support this interpretation. Many graduates described how exposure to industry—often facilitated by their advisors—reshaped their career aspirations. As one respondent explained to us: *"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."*

4.3.3 Advisor Networks and Industry Ties

Lastly, we unpack why the coethnic advisors of immigrant students might be particularly likely to facilitate industry internships. One plausible explanation is that these advisors have stronger ties to industry, especially through ethnically aligned professional networks. Indeed, Figure 5 shows that students whose advisors have stronger industry ties are significantly more likely to undertake an industry internship.

[Figure 5 about here.]

Table 7 presents results that are consistent with this explanation. Specifically, it shows that immigrant-origin advisors—especially those of Asian origin—have a higher intensity of publishing with industry collaborators in the five years before their student's Ph.D. enrollment. This relationship holds even after controlling for the advisor's overall publication count, h-index, institution, department, year, and whether their student is an immigrant.

[Table 7 about here.]

Figure 6 offers further insight into the nature of these collaborations. We compare the U.S. industry coauthors of advisors with Asian versus non-Asian name nationalities. The data show that Asian origin advisors not only collaborate more with industry overall, but that they also have significantly more industry collaborators who are coethnic—that is, they also have Asian name nationalities. In contrast, non-Asian advisors are much less likely to collaborate with Asian origin industry researchers.

[Figure 6 about here.]

These patterns suggest that advisor-industry collaborations are also structured in part by coethnic ties, and that these ties create pipelines for students. Advisors embedded in these networks can create opportunities—such as industry internships—that expose students to an alternate career path besides academia. The coethnic advisors that immigrant students disproportionately match to are more likely to have the (coethnic) industry connections that amplify this endogenous sorting of immigrant Ph.D. graduates into industry roles.

To summarize: our results reveal a distinct advisor-student matching pattern driven by shared backgrounds. These matches, in turn, shape the career trajectories of immigrant students—especially through advisor-driven access to industry internships. This dynamic highlights the role of coethnic, or immigrant-origin, advisors as both gatekeepers and guides in shaping the pathways of the global scientific workforce.

5 Discussion

In this paper, we examine how U.S. universities, and particularly Ph.D. advisors, shape the pathways of highly skilled immigrant talent into the U.S. private sector. Focusing on top Artificial Intelligence (AI) Ph.D. programs, we investigate whether immigrant Ph.D. students disproportionately match with coethnic advisors and whether these advising relationships influence the likelihood of entering industry rather than academia. 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. Using detailed data on AI Ph.D. graduates and their advisors, we document two core findings. First, immigrant students systematically match with coethnic thesis advisors at markedly higher rates than would be expected by chance, a pattern shaped by preferences for shared backgrounds, early contact and reputational spillovers from home country academic networks. Second, immigrant students with coethnic advisors-especially those of Asian origin-are significantly more likely to enter industry than their native counterparts. We find suggestive evidence that this is driven in part by these advisors facilitating industry internships through their professional networks. These findings highlight how Ph.D. programs and, especially faculty with immigrant backgrounds, 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 private sector roles. Building on work that highlights U.S. universities as key channels through which high-skilled immigrants enter the U.S. economy (Bound et al., 2015; Amornsiripanitch et al., 2021), we specify one way in which universities link to firms. We show that coethnic advisor-student pairings play a pivotal role in this process, with immigrant-origin faculty serving not only as attractors of international talent but also as connectors to industry opportunities. 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.

Second, we contribute to the literature on scientists' occupational choices (Stern, 2004; Agarwal and Ohyama, 2013; Roach and Sauermann, 2010, 2024; Sauermann and Roach, 2012, 2014), and specifically to work on how advisor identity shapes career trajectories (Azoulay et al., 2017; Roche, 2023; Gaulé and Piacentini, 2018). We extend this work by showing that coethnic advisor matching constitutes a distinct and underexplored dimension of heterogeneity in career trajectories. Our findings indicate that shared background increases the likelihood of an advisor-student match, particularly among immigrant students, and these matches in turn expose students to advisors with systematically different professional networks. In

our context, immigrant-origin advisors—especially those of Asian descent—are more likely to collaborate with industry researchers and to facilitate internships, which strongly predict students' eventual entry into private-sector roles. In this way, identity-based matching contributes to occupational sorting not through explicit career preferences, but through differentiated exposure to opportunity.

Of note, we identify Ph.D. internships as a central mechanism through which advisors shape occupational sorting. While internships are not often a formal feature of academic training, they represent a concrete exposure point to the private sector. Our findings show that immigrant students with coethnic advisors are significantly more likely to participate in internships, and that this experience is strongly predictive of industry placement. These internships are not incidental—they are facilitated by advisor networks, many of which are structured along coethnic lines. In identifying internships as a key institutional bridge, our study highlights the importance of informal career infrastructure in shaping high-skilled labor market outcomes.

Third, we build on literature on occupational segregation and ethnic clustering (Åslund et al., 2014; Kerr and Kerr, 2021; Kerr and Mandorff, 2023), and connect it to research on pipeline hiring (Brymer et al., 2024). Our contribution lies in tracing identity-based occupational clustering not just at the point of firm hiring, but far upstream, during the training and mentoring phase of the career. The advisor-advisee match, often formed before arrival in the U.S. and shaped by reputational spillovers and prior contact, becomes a key juncture in a self-reinforcing sorting process. In this way, we show that segmentation in professional labor markets is not only a function of demand-side hiring decisions or supply-side preferences—it is also structured by institutional practices of training and mentorship.

This study has some limitations that merit discussion. First, our study focuses on a narrow setting: immigrant Ph.D. graduates of top U.S. programs studying AI-related topics. On the one hand, many of the mechanisms we identify are likely to extend to other domains: coethnic advising relationships, advisor-mediated access to 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. These features may amplify advisor influence on career outcomes and make coethnic matching more salient, as shared networks and prior contact may help navigate a complex and competitive landscape.

That said, the mechanisms we uncover are likely to apply in other fields where immigrants are navigating high-stakes professional environments. In disciplines with lower demand for Ph.D.s in industry, or less international student presence, advisor influence may still be meaningful, but the pathways may differ. For example, in fields such as history or mathematics, where industry options are more limited, coethnic matching may shape trajectories more through academic network access or informal support than through

industry internship facilitation. Our findings are therefore most likely to generalize to STEM fields, especially those undergoing rapid change or where the 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 and explore additional dimensions of advisor influence within AI—such as how advisors shape students' research agendas or leave lasting imprints on their long-term trajectories.

Second, our findings are driven largely by the behavior and outcomes of Asian immigrants, who make up the majority of international students in AI and represent a high proportion of both immigrant Ph.D. graduates and faculty in our sample. As such, the patterns we document—particularly the high prevalence of coethnic advisor matching and the strong advisor influence on industry placement—are clearest in this group. Asian immigrants may be uniquely positioned in this context due to their numerical presence, relatively well-established coethnic academic networks in top U.S. institutions, and cultural or institutional distance from the U.S., which may heighten the value of shared background in the advising relationship. These factors may all make coethnic advising both more likely and more consequential for this group.

However, the underlying mechanisms we identify are not likely to be exclusive to Asian immigrants. In fields or institutions where other immigrant groups are more heavily represented, similar dynamics may emerge. That said, for smaller immigrant groups with less representation among U.S. faculty, coethnic advising may be less available, and when it occurs, it may be more driven by idiosyncratic connections than by structural pipelines. As such, we would expect the prevalence of coethnic matching to be lower, and its career consequences potentially more variable, for non-Asian immigrants. Moreover, immigration-related incentives could shape how coethnic advising influences both the Ph.D. experience and occupational choices. Future research should explore how these dynamics play out across different immigrant groups. These limitations notwithstanding, our findings offer broader insights into how universities and firms together shape the movement of global scientific talent—and the institutional mechanisms that influence where that talent ultimately ends up.

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, coethnic 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.

Our findings also highlight a growing challenge for universities. As an increasing number of Ph.D. students, particularly top immigrant talent, transition into industry—often facilitated by coethnic advisors—universities may face increasing difficulty filling academic positions, particularly in high-demand

fields like AI. This shift is already evident in the movement of AI research from academia to industry (Ahmed et al., 2023). These dynamics underscore the fragility of the current talent pipeline: just as universities may face challenges retaining future faculty, broader immigration constraints threaten the continued inflow of global scientific talent into both academia and industry.

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. Ph.D. 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.

To better understand the magnitude of these potential disruptions, we conduct a set of back-of-the-envelope calculations. Among immigrant Ph.D. graduates in our sample, 65% take an industry job in their first position post-Ph.D, compared to 51% of native graduates. 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 Ph.D.-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 Ph.D.s would fall from 6.5 to 5.1. This shortfall matters not only for workforce size but also for innovative output: in Appendix Figure A5, 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.

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 coethnic 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.

References

Agarwal, R. and Ohyama, A. (2013). Industry or academia, basic or applied? career choices and earnings trajectories of scientists. *Management Science*, 59(4):950–970.

Agrawal, A., Cockburn, I., and McHale, J. (2006). Gone but not forgotten: knowledge flows, labor mobility, and enduring social relationships. *Journal of Economic Geography*, 6(5):571–591.

Ahmed, N., Wahed, M., and Thompson, N. C. (2023). The growing influence of industry in ai research. *Science*, 379(6635):884–886.

Amornsiripanitch, N., Gompers, P. A., Hu, G., and Vasudevan, K. (2021). Getting schooled: the role of universities in attracting immigrant entrepreneurs. Technical report, National Bureau of Economic Research.

Amuedo-Dorantes, C. and Furtado, D. (2019). Settling for Academia? H-1B Visas and the Career Choices of International Students in the United States. *Journal of Human Resources*.

Åslund, O., Hensvik, L., and Skans, O. N. (2014). Seeking similarity: How immigrants and natives manage in the labor market. *Journal of Labor Economics*, 32(3):405–441.

Azoulay, P., Liu, C. C., and Stuart, T. E. (2017). Social influence given (partially) deliberate matching: Career imprints in the creation of academic entrepreneurs. *American Journal of Sociology*, 122(4):1223–1271.

Bauer, R., Koedijk, K., and Otten, R. (2005). International evidence on ethical mutual fund performance and investment style. *Journal of banking & finance*, 29(7):1751–1767.

Beerli, A., Ruffner, J., Siegenthaler, M., and Peri, G. (2021). The abolition of immigration restrictions and the performance of firms and workers: evidence from switzerland. *American Economic Review*, 111(3):976–1012.

Bernstein, S., Diamond, R., Jiranaphawiboon, A., McQuade, T., and Pousada, B. (2022). The contribution of high-skilled immigrants to innovation in the united states. Technical report, National Bureau of Economic Research.

Bound, J., Demirci, M., Khanna, G., and Turner, S. (2015). Finishing Degrees and Finding Jobs: U.S. Higher Education and the Flow of Foreign IT Workers. In *Innovation Policy and the Economy*, volume 15, pages 27–72.

Brinatti, A., Chen, M., Mahajan, P., Morales, N., and Shih, K. Y. (2023). The impact of immigration on firms and workers: Insights from the h-1b lottery. *Available at SSRN*, 4431106.

Brymer, R., Paraskevas, J.-P., Josefy, M., and Ellram, L. (2024). Pipeline hiring's effects on the human capital and performance of new recruits. *Strategic Management Journal*, 45(9):1822–1850.

Cadena, B. C., Kovak, B. K., Lessem, R., and Li, S. (2017). Migration networks and mexican migrants' spatial mobility in the us.

Choudhury, P. and Kim, D. Y. (2019). The ethnic migrant inventor effect: Codification and recombination of knowledge across borders. *Strategic Management Journal*, 40(2):203–229.

Dustmann, C., Glitz, A., Schönberg, U., and Brücker, H. (2016). Referral-based job search networks. *The Review of Economic Studies*, 83(2):514–546.

Finn, M. (2010). Stay Rates of Foreign Doctorate Recipients from U.S. Universities, 2007. Technical report.

Freeman, R. B. and Huang, W. (2015). Collaborating with people like me: Ethnic coauthorship within the united states. *Journal of Labor Economics*, 33(S1):S289–S318.

Ganguli, I. and Gaulé, P. (2019). Will the us keep the best and the brightest (as postdocs)? career and location preferences of foreign stem phds. In *The Roles of Immigrants and Foreign Students in US Science, Innovation, and Entrepreneurship*, pages 49–69. University of Chicago Press.

Gaulé, P. and Piacentini, M. (2013). Chinese graduate students and us scientific productivity. *Review of Economics and Statistics*, 95(2):698–701.

Gaulé, P. and Piacentini, M. (2018). An advisor like me? Advisor gender and post-graduate careers in science. *Research Policy*, 47(4):805–813.

Glennon, B., Morales, F., Carnahan, S., and Hernández, E. (2024). Does Employing Skilled Immigrants Enhance Competitive Performance? Evidence from European Football Clubs. *Management Science*.

Hernandez, E. and Kulchina, E. (2020). Immigrants and foreign firm performance. *Organization Science*, 31(4):797–820.

Hunt, J. (2011). Which immigrants are most innovative and entrepreneurial? distinctions by entry visa. *Journal of Labor Economics*, 29(3):417–457.

Kalnins, A. and Chung, W. (2006). Social capital, geography, and survival: Gujarati immigrant entrepreneurs in the us lodging industry. *Management science*, 52(2):233–247.

Kerr, S. P. and Kerr, W. R. (2021). Whose job is it anyway? Coethnic hiring in new us ventures. In *Journal of Human Capital*, volume 15, pages 86–127.

Kerr, W. R. (2008). Ethnic scientific communities and international technology diffusion. *The Review of Economics and Statistics*, 90(3):518–537.

Kerr, W. R. and Lincoln, W. F. (2010). The supply side of innovation: H-1b visa reforms and us ethnic invention. *Journal of Labor Economics*, 28(3):473–508.

Kerr, W. R. and Mandorff, M. (2023). Social networks, ethnicity, and entrepreneurship. *Journal of Human Resources*, 58(1):183–220.

Kerr, W. R., Mandorff, M., Basker, E., Becker, G., Beine, M., Bengtsson, O., Bruze, G., Carlton, D., Chiswick, B., Fairlie, R., Gentzkow, M., Haltiwanger, J., Iantchev, E., Janson, S., Kaur, M., Lalley, S., Le Brun, A., Mathew, B., Nguyen, T., Protsyk, A., Rubinstein, Y., Shapiro, J., Soloveichik, R., Syverson, C., Thomas, C., Topel, R., and Wormald, N. (2021). Social Networks, Ethnicity, and Entrepreneurship.

Marinoni, A. (2023). Immigration and entrepreneurship: The role of enclaves. *Management Science*, 69(12):7266–7284.

Nanda, R. and Khanna, T. (2010). Diasporas and domestic entrepreneurs: Evidence from the indian software industry. *Journal of Economics & Management Strategy*, 19(4):991–1012.

Patel, K. and Vella, F. (2013). Immigrant networks and their implications for Occupational choice and wages. *Review of Economics and Statistics*, 95(4):1249–1277.

Rauch, J. E. and Trindade, V. (2002). Ethnic chinese networks in international trade. *Review of Economics and Statistics*, 84(1):116–130.

Roach, M. and Sauermann, H. (2010). A taste for science? phd scientists' academic orientation and self-selection into research careers in industry. *Research Policy*, 39(3):422–434.

Roach, M. and Sauermann, H. (2024). Can technology startups hire talented early employees? ability, preferences, and employee first job choice. *Management Science*, 70(6):3619–3644.

Roach, M., Sauermann, H., and Skrentny, J. (2019). Are Foreign STEM PhDs More Entrepreneurial? Entrepreneurial Characteristics, Preferences, and Employment Outcomes of Native and Foreign Science and Engineering PhD Students. In *The Roles of Immigrants and Foreign Students in US Science, Innovation, and Entrepreneurship*, pages 207–228. University of Chicago Press.

Roach, M. and Skrentny, J. (2019). Why foreign stem phds are unlikely to work for us technology startups. *Proceedings of the National Academy of Sciences*, 116(34):16805–16810.

Roche, M. P. (2023). Academic entrepreneurship: Entrepreneurial advisors and their advisees' outcomes. *Organization Science*, 34(2):959–986.

Sauermann, H. and Roach, M. (2012). Science phd career preferences: levels, changes, and advisor encouragement. *PloS One*, 7(5):e36307.

Sauermann, H. and Roach, M. (2014). Not all scientists pay to be scientists: PhDs' preferences for publishing in industrial employment. *Research Policy*, 43(1):32–47.

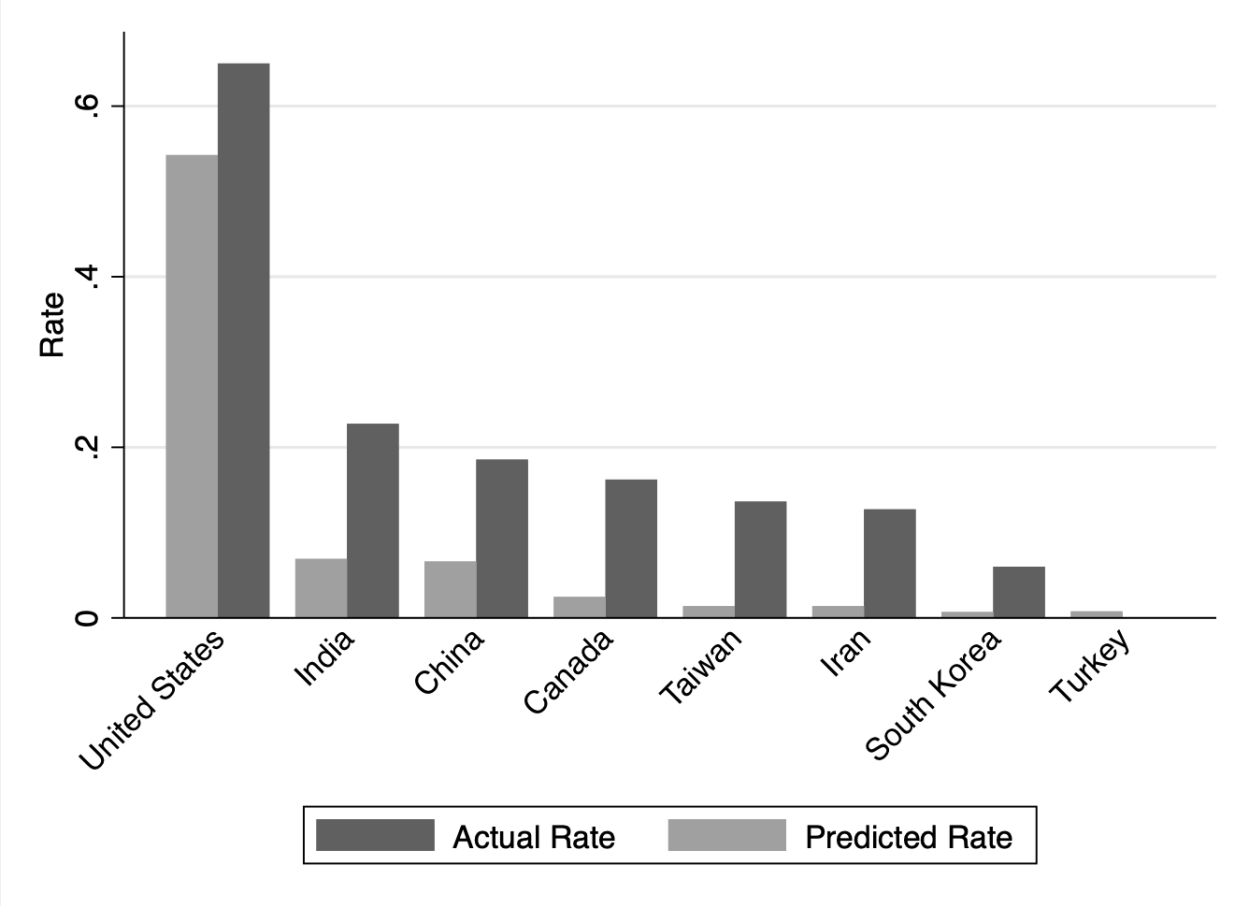
Stephan, P. E. and Levin, S. G. (2001). Exceptional contributions to us science by the foreign-born and foreign-educated. *Population research and Policy review*, 20:59–79.

Stern, S. (2004). Do scientists pay to be scientists? *Management Science*, 50(6):835–853.

Zellner, C. (2003). The economic effects of basic research: Evidence for embodied knowledge transfer via scientists' migration. *Research Policy*, 32(10):1881–1895.

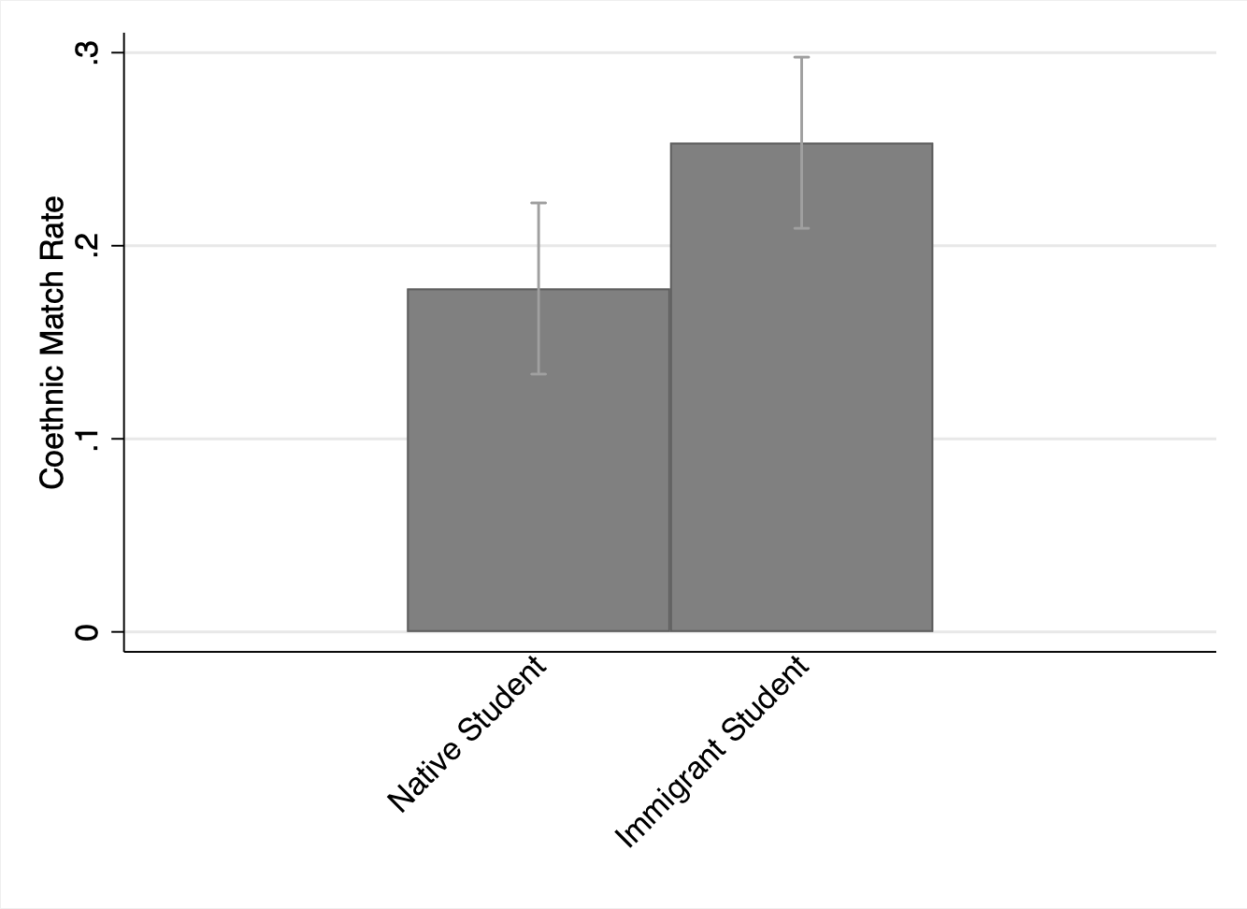
Zucker, L. G., Darby, M. R., and Armstrong, J. S. (2002). Commercializing knowledge: University science, knowledge capture, and firm performance in biotechnology. *Management science*, 48(1):138–153.

Figure 1: Predicted and Actual Rate of Coethnic Matching



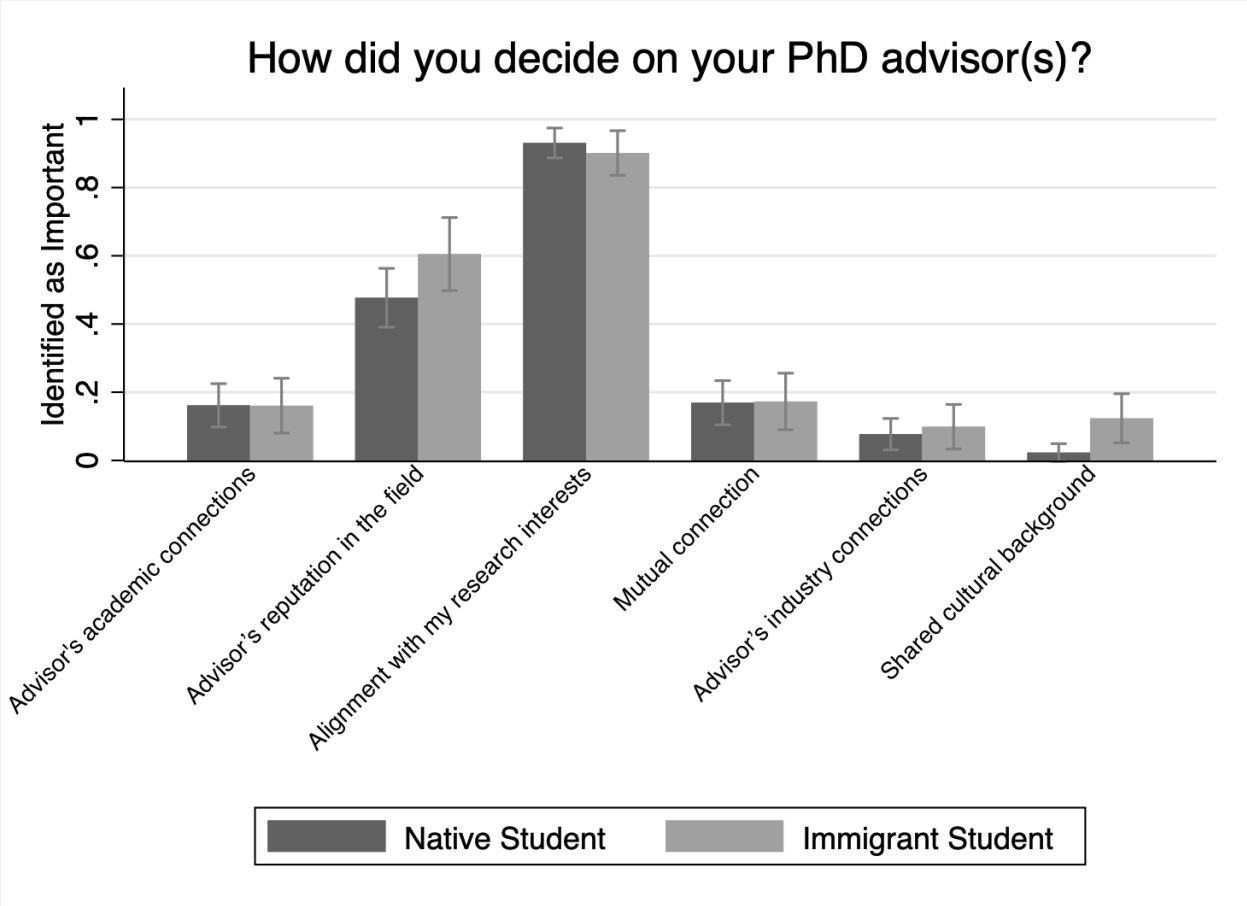
Notes: Predicted matching rates assume random assignment of students to advisors, presenting the proportion of advisors in our sample who obtained their undergraduate degree from each country. Actual matching rates reflect the share of sample graduates from each country with advisors from the same undergraduate country in each of the top eight represented countries.

Figure 2: Coethnic Advisor Matching Rate



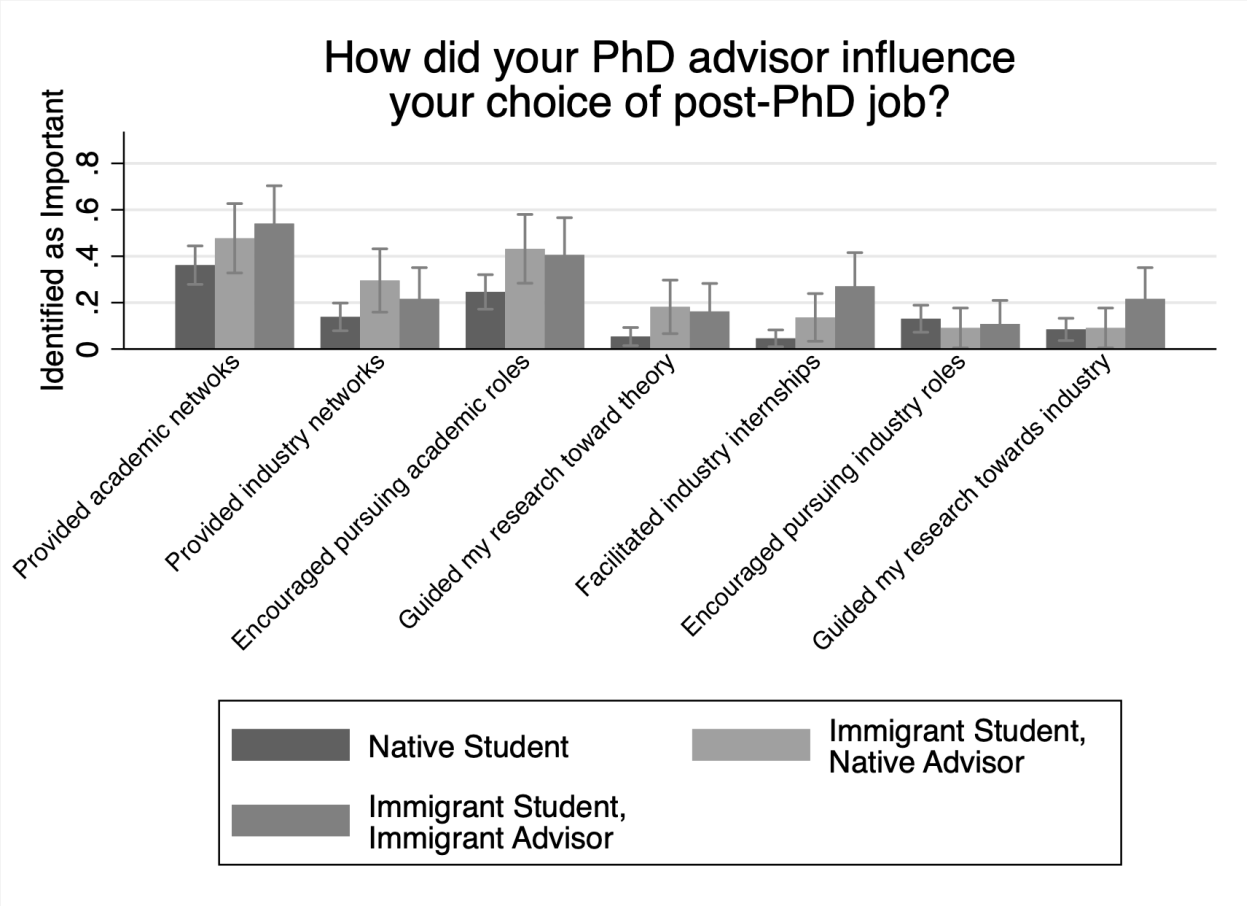
Notes: We plot the coefficient estimates from regressing an indicator variable that takes the value of 1 if the focal student has an advisor with the same name nationality classification on an indicator variable for whether the focal student is an immigrant, holding constant fixed effects for each name nationality, Ph.D. institution, Ph.D. department, and graduation year, as well as a full set of controls for advisor and student pre-Ph.D. productivity and industry connections. The corresponding table is Appendix Table A5. Standard errors are clustered at the level of the advisor

Figure 3: Advisor Selection Criteria



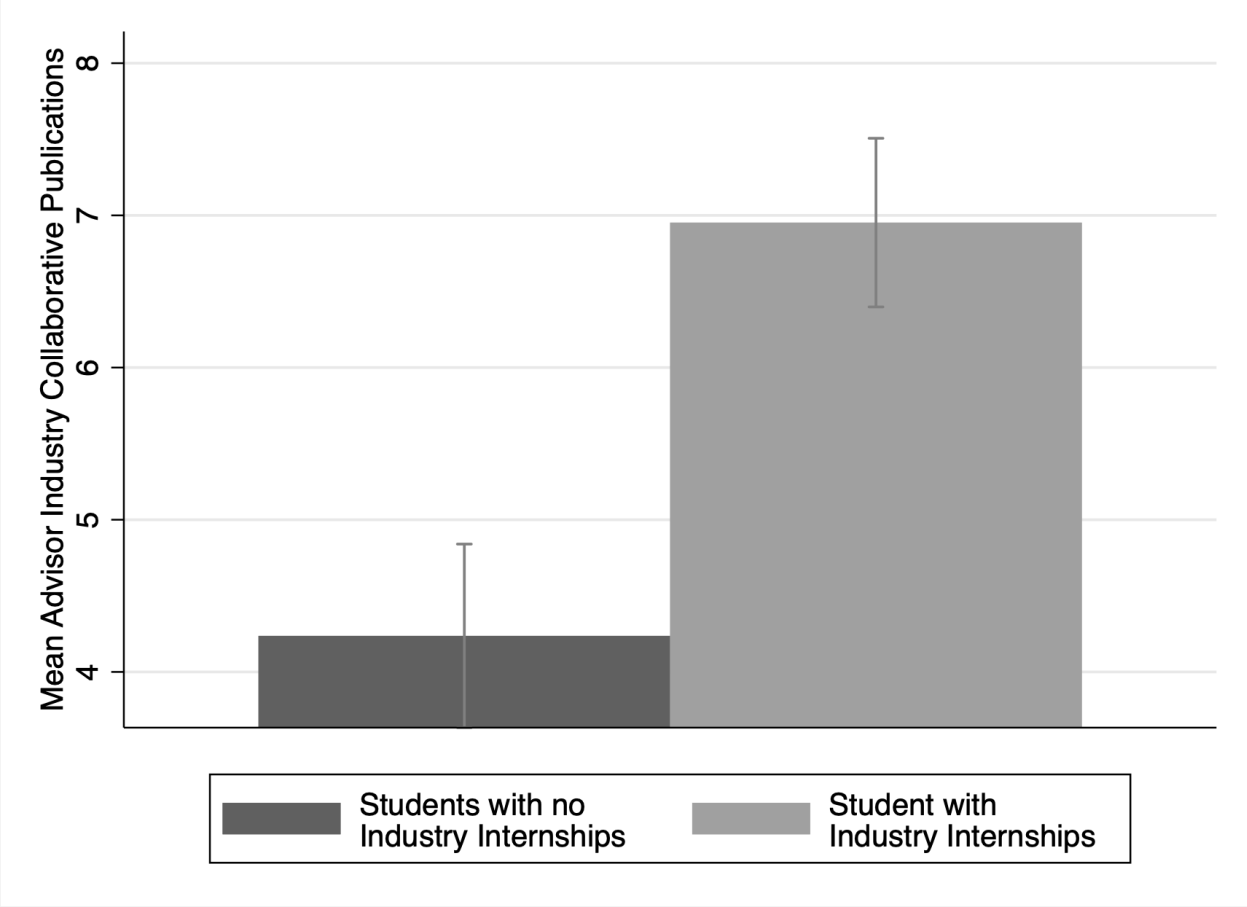
Notes: Ph.D. graduates were asked: How did you decide on your Ph.D. advisor(s)? Please select the top (up to) three most important factors. They chose from: Shared cultural background, cultural familiarity, or language considerations (if applicable); Advisor's industry connections (e.g., relationships with companies, potential for internships or post-Ph.D. positions); Advisor's academic connections (e.g., collaborations with other researchers, access to prestigious networks); Advisor's reputation in the field (e.g., prominence, citation impact); Mutual connection or shared professional network; Alignment with my research interests (e.g., expertise in my area of focus). For each option, we plot the average share of respondents who selected it (coded as 1 if selected, 0 otherwise), with averages and confidence intervals shown separately for native and immigrant students.

Figure 4: Advisor Influence on Career Pathways



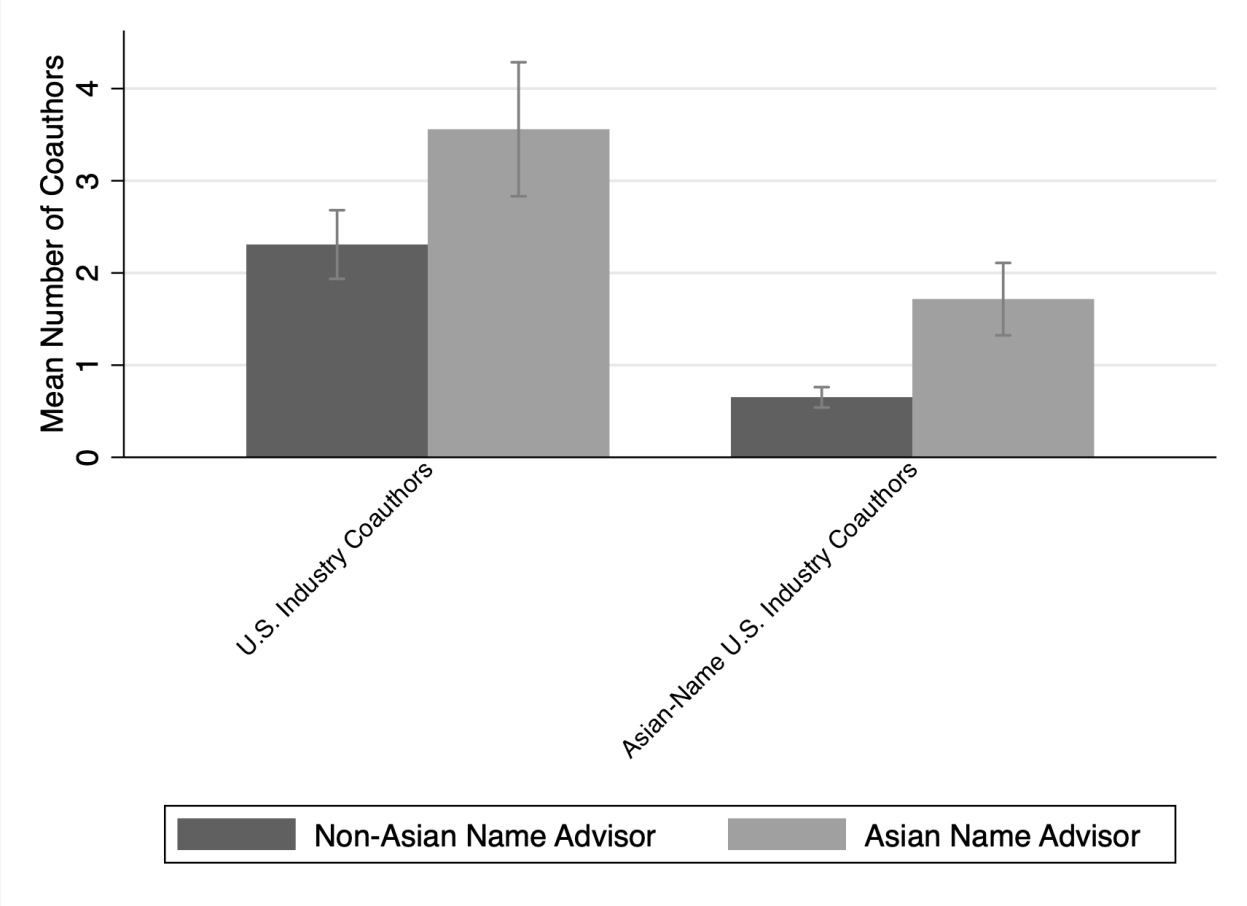
Notes: Graduates were asked: How did your Ph.D. advisor influence your choice of post-Ph.D. job? (Select all that apply). They selected from: Encouraged pursuing academic roles; Provided academic networking opportunities (e.g., conferences, introductions to academic coauthors and researchers); Guided my research towards more theoretical questions; Encouraged pursuing industry roles; Guided my research towards industry applications; Provided industry networking opportunities (e.g., introductions to industry professionals, alumni, or coauthors); Facilitated industry internships. For each option, we plot the average share of respondents who selected it (coded as 1 if selected, 0 otherwise), with averages and confidence intervals shown separately for native students, immigrant students with native advisors, and immigrant students with immigrant advisors.

Figure 5: Advisor Industry Coauthored Publications and Student Industry Internships



Notes: We plot the average number of industry coauthored publications by students' advisors in the five years before Ph.D. start, comparing students who did and did not have an industry internship during their Ph.D. Confidence intervals shown.

Figure 6: Advisor Industry Coauthors



Notes: We plot the average number (with confidence intervals) of unique U.S. industry coauthors for each advisor in the five years before their first student in our sample began a Ph.D., broken out by the name-ethnicity of coauthors. Each advisor is represented only once, based on the first year they had a student begin a Ph.D. in our sample.

Table 1: Graduating Institution for Study Sample AI Graduates

	Nb Sample Graduates	Immigrant Percentage
Overall	1,769	0.52
Institution		
California Institute of Technology	14	0.71
Carnegie Mellon University	54	0.63
Columbia University	80	0.50
Cornell University	68	0.47
Georgia Institute of Technology	61	0.56
Harvard University	34	0.41
Massachusetts Institute of Technology	174	0.42
Princeton University	62	0.48
Stanford University	193	0.36
The University of Texas at Austin	9	0.67
The University of Wisconsin - Madison	69	0.58
University of California, Berkeley	154	0.42
University of California, Los Angeles	64	0.63
University of Illinois	97	0.69
University of Maryland, College Park	131	0.68
University of Massachusetts Amherst	129	0.53
University of Michigan	78	0.56
University of Pennsylvania	70	0.46
University of Southern California	96	0.81
University of Washington	132	0.42
Department		
Biology	40	0.33
Chemistry	26	0.23
Computer Science	407	0.58
Engineering	786	0.60
Environmental Science	4	0.75
Geology	11	0.18
Materials Science	16	0.50
Mathematics	148	0.47
Medicine	87	0.29
Physics	41	0.37
Other Non-S&E	203	0.37
Post-Graduation First Employer		
Google	121	0.67
Facebook	64	0.73
Stanford University	47	0.53
Microsoft	46	0.63
Amazon	30	0.77
Massachusetts Institute of Technology	23	0.52
Apple	23	0.78
Princeton University	23	0.48
Harvard University	21	0.43
University of Washington	21	0.38

Notes: The underlying data are from CSET and consist of 1,769 artificial intelligence Ph.D. graduates from the top twenty U.S. institutions. Column 1 (Nb Sample Graduates) is the count of graduates in each category. Column 2 (Immigrant Pecentage) is the percentage of graduates who are immigrants, as defined by the location of their undergraduate institution.

Table 2: Descriptive Statistics

	Native (N = 847) (1)		Immigrant (N = 922) (2)		(2)-(1)
	mean	std. dev.	mean	std. dev.	mean (std. dev.)
Ph.D. graduation year	2016	1.41	2016	1.38	0.016 (0.066)
Top 5 Ph.D. institution	0.48	0.50	0.32	0.48	-0.16*** (0.023)
Pre-Ph.D. graduation number of publications	4.35	7.66	7.19	9.59	2.84*** (0.42)
Any immigrant advisor	0.33	0.47	0.53	0.50	0.20*** (0.023)
Average advisor industry collaborative publications	4.56	7.05	7.33	10.37	2.77*** (0.43)
Work in U.S. post Ph.D. graduation	0.94	0.24	0.92	0.28	-0.022* (0.012)
First job industry	0.51	0.50	0.65	0.48	0.14*** (0.023)
First job academia	0.43	0.50	0.33	0.47	-0.10*** (0.023)

Notes: This sample consists of 1,769 artificial intelligence U.S. Ph.D. graduates. Native and immigrant students are defined using the location of their undergraduate institution.

Table 3: Advisor Matching

	Advisor with Non-U.S. Undergraduate		Advisor with Asian Undergraduate		Advisor with Asian Name Ethnicity		Advisor With Same Undergraduate Country, Just Immigrant Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigrant	0.1511***	0.1354***						
	(0.025)	(0.025)						
Asian Immigrant			0.1730***	0.1565***	0.1810***	0.1641***	0.0821***	0.0784***
			(0.023)	(0.022)	(0.026)	(0.026)	(0.024)	(0.024)
Non-Asian Immigrant			0.0367	0.0291	0.0230	0.0150		
			(0.024)	(0.022)	(0.027)	(0.026)		
Total Observations	1769	1769	1769	1769	1769	1769	922	922
Mean of Dep. Variable	0.4358	0.4358	0.1826	0.1826	0.2459	0.2459	0.1464	0.1464
Graduation Year FE	X	X	X	X	X	X	X	X
PhD Department FE	X	X	X	X	X	X	X	X
PhD Institution FE	X	X	X	X	X	X	X	X
Pre-PhD Publications		X		X		X		X
Pre-PhD Industry Job		X		X		X		X
Advisor Industry Publications		X		X		X		X
Advisor H-index		X		X		X		X

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

Notes: [a] Estimates stem from OLS regressions in which the dependent variables are the corresponding column title, set equal to one if the focal student has an advisor of the given type. The regression is at the level of the sample Ph.D. graduate. Immigrant is non-U.S. undergraduate. Asian immigrant and advisor name nationality include those with undergraduate degrees (or name nationality) from China, India, Taiwan, Cambodia, Japan, South Korea, Malaysia, Pakistan, Thailand and Vietnam. Publication counts and advisor h-index are transformed using inverse hyperbolic sine. [b] Heteroskedastic robust standard errors clustered at the level of the advisor are given in parentheses.

Table 4: Industry Job Placement

	Industry First Job			
	(1)	(2)	(3)	(4)
Immigrant	0.1142***		0.0885***	0.0894***
	(0.026)		(0.030)	(0.029)
Asian Immigrant		0.1548***		
		(0.027)		
Non-Asian Immigrant		0.0452		
		(0.035)		
Immigrant × Coethnic Advisor			0.0863*	0.0610
			(0.052)	(0.055)
Asian Name Nationality Advisor				0.0389
				(0.031)
Total Observations	1769	1769	1769	1769
Mean of Dep. Variable	0.5822	0.5822	0.5822	0.5822
Graduation Year FE	X	X	X	X
PhD Department FE	X	X	X	X
PhD Institution FE	X	X	X	X
Pre-PhD Publications	X	X	X	X
Pre-PhD Industry Job	X	X	X	X
PhD Publications	X	X	X	X

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

Notes: [a] Estimates are from OLS regressions in which the dependent variable is a dummy variables that takes the value of 1 if the graduate takes an industry job as their first post-Ph.D. job, and 0 otherwise. The regression is at the level of the sample Ph.D. graduate. Coethnicity is based on our preferred measure using matching name nationality. Publication counts and advisor h-index are transformed using inverse hyperbolic sine. [b] Heteroskedastic robust standard errors clustered at the level of the advisor are given in parentheses.

Table 5: During Ph.D. activities

	During-PhD Industry Employment	During-PhD Industry Collaborative Publications	Mean Industry Use of During-PhD Publication Concepts
	(1)	(2)	(3)
Immigrant	0.1039***	0.1052***	0.0077*
	(0.027)	(0.034)	(0.004)
Immigrant × Coethnic Advisor	0.0851*	0.0105	0.0015
	(0.050)	(0.064)	(0.007)
Total Observations	1769	1769	862
Mean of Dep. Variable	0.6501	5.8321	0.1606
Graduation Year FE	X	X	X
PhD Department FE	X	X	X
PhD Institution FE	X	X	X
Pre-PhD Publications	X	X	X
Pre-PhD Industry Job	X	X	X

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

Notes: [a] Estimates are from OLS regressions in which the dependent variable corresponds to the column headings: a dummy variable that takes the value of 1 if the graduate has industry employment during their Ph.D. (column 1); inverse hyperbolic sine-transformed publication counts with at least one industry coauthor during Ph.D. (column 2); and inverse hyperbolic sine-transformed use of industry concepts during Ph.D.(column 3). Industry concepts are defined as the ratio of U.S.-based publications using that concept authored by industry researchers to those authored by academic researchers, measured in the graduate's year of graduation. A higher number can be interpreted to mean that it is a concept used relatively more frequently in industry as compared to academia. Column (3) only includes Ph.D. graduates who have a publication record in the five years prior to graduation. Coethnicity is based on our preferred measure using matching name nationality. Publication counts and advisor h-index are transformed using inverse hyperbolic sine. Regressions are at the unit of the Ph.D. graduate. [b] Heteroskedastic robust standard errors clustered at the level of the advisor are given in parentheses.

Table 6: Drivers of Industry Employment

	Industry First Job			
	(1)	(2)	(3)	(4)
Immigrant	0.0885***	0.0180	0.0885***	0.0828***
	(0.030)	(0.022)	(0.030)	(0.029)
Immigrant × Coethnic Advisor	0.0863*	0.0283	0.0863*	0.0825
	(0.052)	(0.039)	(0.052)	(0.052)
During-PhD Industry Employment		0.6818***		
		(0.020)		
During-PhD Industry Collaborative Publications			-0.0444**	
			(0.021)	
Mean Industry Use of During-PhD Publication Concepts				1.6292***
				(0.306)
Total Observations	1769	1769	1769	1769
Mean of Dep. Variable	0.5822	0.5822	0.5822	0.5822
Graduation Year FE	X	X	X	X
PhD Department FE	X	X	X	X
PhD Institution FE	X	X	X	X
Pre-PhD Publications	X	X	X	X
Pre-PhD Industry Job	X	X	X	X
PhD Publications	X	X	X	X

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

Notes: [a] Estimates are from OLS regressions in which the dependent variable is a dummy variable that takes the value of 1 if the graduate takes an industry job as their first post-Ph.D. job, 0 otherwise. Coethnicity is based on our preferred measure using matching name nationality. All publication counts and the mean industry proportion variables are transformed using inverse hyperbolic sine. Regressions are at the unit of the Ph.D. graduate. All publication counts and concept proportion counts are inverse hyperbolic sine transformed. [b] Heteroskedastic robust standard errors clustered at the level of the advisor are given in parentheses.

Table 7: Advisor Orientation

	Advisor Industry Collaborative Publications					
	(1)	(2)	(3)	(4)	(5)	(6)
Non-U.S. Undergraduate Advisor	0.2265***	0.1951***				
	(0.071)	(0.071)				
Immigrant Student		0.1822***		0.1697**		0.1681**
		(0.069)		(0.068)		(0.068)
Asian Undergraduate Advisor			0.4007***	0.3630***		
			(0.099)	(0.099)		
Non-Asian Undergraduate Advisor			0.0817	0.0581		
			(0.076)	(0.078)		
Asian Name Ethnicity Advisor					0.3974***	0.3719***
					(0.084)	(0.084)
Total Observations	1472	1472	1472	1472	1472	1472
Mean of Dep. Variable	4.8329	4.8329	4.8329	4.8329	4.8329	4.8329
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
Advisor 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 are from Poisson Maximum Likelihood regressions where the dependent variable is the count of publications coauthored with industry collaborators, in the five years prior to the sample Ph.D. students' start of PhD. Duplicate advisors are dropped, retaining just the first year they had a student start the Ph.D. Regressions are at the unit of the Ph.D. advisor. [b] Heteroskedastic robust standard errors clustered at the level of the university department are given in parentheses.