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Regular Article

Top Talent, Elite Colleges, and Migration: Evidence from the Indian Institutes of Technology☆

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ABSTRACT

We study migration in the right tail of the talent distribution using a novel dataset of Indian high school students taking the Joint Entrance Exam (JEE), a college entrance exam used for admission to the prestigious Indian Institutes of Technology (IIT). We find a high incidence of migration after students complete college: among the top 1000 scorers on the exam, 36% have migrated abroad, rising to 62% for the top 100 scorers. We next document that students who attended the original "Top 5" IIT were 5 percentage points more likely to migrate for graduate school compared to equally talented students who studied in other institutions. We explore two mechanisms for these patterns: signaling, for which we study migration after one university suddenly gained the IIT designation; and alumni networks, using information on the location of IIT alumni in U.S. computer science departments.

1. Introduction

Highly skilled immigrants make important contributions to innovation and technology in the United States. Often, they study in elite universities in their home countries before getting advanced degrees abroad. For example, many successful Indian immigrants in the technology industry—including Sundar Pichai, the CEO of Alphabet Inc./Google, and Arvind Krishna, the CEO of IBM—are undergraduate alumni of the selective Indian Institutes of Technology (IITs). Similarly, Chinese students in U.S. Ph.D. programs overwhelmingly come from a set of highly selective Chinese universities (Gaulé and Piacentini, 2013).

In this paper, we study migration in the very right tail of the talent distribution for high school students in India, focusing on the extent to which elite universities in their home country facilitate migration. We focus on the Indian Institutes of Technology (IITs). The IITs are prestigious and highly selective technical universities with lower acceptance rates than Ivy League colleges, particularly for the original five IIT Campuses.[1] Admission to the IITs is solely through the Joint Entrance Exam (JEE), where nearly one million exam takers compete for less than ten thousand spots. Desai et al. (2009) document anecdotal evidence related to the role of elite institutions in India, such as the IITs and the All India Institute of Medical Sciences, in facilitating skilled migration to the United States. IIT students have even been described as "America's most valuable import from India" (Leung, 2003).

Emigration is often difficult to observe from administrative datasets, and few surveys have been conducted with a focus on top talent that are not selected on future success or mobility.[2] We were able to overcome these challenges by leveraging the unanticipated public release of the

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[1] IIT Kharagpur, IIT Bombay, IIT Madras, IIT Kanpur and IIT Delhi. Source regarding selectivity: Leung, Rebecca, "Imported From India," June 19, 2003, https://www.cbsnews.com/news/imported-from-india/, accessed August 22, 2021.

[2] Survey evidence of Indian academics suggests that academic performance and educational institutions attended matter for later international mobility, but focusing on academics leads to a sample more likely to be mobile and selected on later success (Czaika and Toma, 2017).

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names and scores of JEE exam takers in 2010, combined with an intensive manual collection effort on exam takers' outcomes. The result is a novel dataset of high school students who took the JEE exam, linked to college attended and later career, education, and migration outcomes. The data provides individuals' scores received on the exam and their national ranking. An important feature of the data is that we can observe the whole set of IITs and majors an individual could have chosen to attend, since admission to an IIT and a major course of study are based solely on the JEE score.

First, we document a salient correlation between an individual's score on the JEE exam and migration up to eight years later among the top exam takers. Among the top 100 scorers, for instance, 62% have migrated abroad, primarily to the U.S. and for graduate school. Among the top 1000 scorers, 36% have migrated abroad, which is still sizeable but much lower.

Among students in the top end of the score distribution (top 0.2% of test takers), we find that holding JEE score fixed, those who attended one of the five most prestigious IITs are 4 percentage points more likely to migrate than equally high-scoring students who attended other universities. These similarly talented students attended other institutions in the IIT system, such as IIT Roorkee, IIT Guwahati, or BHU Varanasi, which are organized along similar lines but are relatively less prestigious. The effects are mainly driven by migrating for graduate school and a Ph.D., specifically, while there is no significant effect for migrating for work.[3]

We next investigate what mechanisms can explain these patterns. First, we examine whether, among students with identical JEE scores, if those who attend a Top 5 IIT are likely to select different majors, thus providing students with different types of human capital. While students attending a Top 5 do have different majors on average compared to those who do not, we obtain similar results when we control for the major area of study. Second, elite universities could be a signal of quality, effectively solving an information friction about a potential migrant's ability or quality of their human capital to future employers or graduate programs. To explore the role of signaling, we leverage a natural experiment when one institution (Institute of Technology, Banaras Hindu University (IT-BHU)) unexpectedly received IIT status, without any concomitant changes to its staff or curriculum.[4] Comparing students who enrolled at BHU before the change was made, we find that students who (plausibly exogenously) received an IIT degree were 10 percentage points more likely to migrate than those of preceding cohorts.

The BHU experience allows us to separately identify the signaling value of an IIT degree, as the quality of education/human capital acquired by the students in the cohorts before and after the change remained constant, while only the name of the university on the degree received differed. Importantly, the unanticipated nature of the change implies that we are comparing students who were not expecting to receive an IIT degree and would be similar in terms of unobservable factors such as motivation or ambition.

Another possible mechanism is that students attending elite universities may become part of a network of successful alumni and faculty, many of whom have migrated, and this network can facilitate migration. Prior literature has shown the role of such diaspora networks in lowering migration costs and increasing migration flows, but this literature has not focused on extremely highly skilled migrant networks as we do here (Beine et al., 2011). To examine the role of networks, we conduct a case study of which U.S. computer science Ph.D. programs IIT graduates attend. We find that the number of alumni of one's own IIT among a U.S. computer science department's faculty is positively associated with attending that department for a Ph.D. By contrast, we find no such association for the number of alumni of other IITs.

Overall, our results suggest that elite schools play a key role in shaping migration outcomes, both in terms of the overall propensity and the particular migration destination. The BHU evidence suggests that the quality of acquired human capital does not appear to be the mechanism driving this phenomenon. Our evidence, rather, supports the view of elite education as mainly signaling a potential migrant's ability or quality of their human capital, and providing access to valuable networks. U.S. graduate programs—a key pathway for migration—are especially keen to recruit the best and brightest. However, to identify the best and brightest, they must rely on external information and signals, and elite home universities may provide these.

Our paper contributes to the literature on the international migration of highly skilled individuals. International migration, particularly high-skilled migration, is often facilitated by institutional actors. Recent literature has documented the important role firms play in facilitating skilled migration (Kerr and Lincoln, 2010; Clemens, 2013; Kerr et al., 2015; Choudhury and Kim, 2019). In this paper, we argue that other institutional actors, i.e., elite universities, play an important role in facilitating skilled migration of talent from emerging to developed countries.[5]

While prior migration literature has documented the role of universities from the demand side (e.g., Borjas and Doran, 2012, 2015; Amornsiripanitch et al., 2021) and the significant enrollment of students from India in U.S. graduate programs (Bound et al., 2021), arguably an important gap remains relative to studying elite universities from the supply side, i.e., as facilitators of skilled migration. In particular, while Kerr, Kerr, Özden, and Parsons (2016) postulate that host country universities facilitate high-skilled migration through admission decisions, our paper additionally sheds light on the agency of home country elite universities in facilitating high-skilled migration through the twin mechanisms of signaling and networks.

Our paper also complements extant literature that studies high-skilled migrants in the context of U.S. universities (e.g., Kahn and MacGarvie, 2020), the literature on migration patterns of the best and brightest academic performers from other countries (e.g., Gibson and McKenzie, 2011; Gibson and McKenzie, 2012; Agarwal et al., 2023) and the literature on skill selectivity of migrants (Saint-Paul, 2004; Docquier and Marfouk, 2006; Docquier and Rapoport, 2012; Grogger and Hanson, 2011; Kerr et al., 2016).

Finally, our paper contributes to the literature on the labor market returns to attending selective colleges. In general, the findings on the impact of attending an elite college have been mixed (e.g., Dale and Krueger, 2002; Pop-Eleches and Urquiola, 2013; Abdulkadiroğlu et al., 2014; Zimmerman, 2019). Interestingly, this literature tends not to find effects of college selectivity on earnings in the U.S., but some effects on earnings and career outcomes in Italy (Anelli, 2020) and in several developing country contexts, including Chile (Zimmerman, 2019), India (Sekhri, 2020; Bertrand et al., 2010) and Colombia (Barrera-Osorio and

[3] In order to develop a better understanding of the drivers of migration for work in this setting, we conducted several field interviews with placement offices at the IITs. Our interviews revealed that top multinationals had been hiring IIT graduates for their local subsidiaries in India well before the period of study (e.g., McKinsey in 1992, BCG in 1995, Microsoft in 1990, Goldman Sachs in 2006), while the American offices of these firms were explicitly barred from recruiting directly from the IITs. Individuals who migrated to the U.S. for work often do so by transferring within these companies (or after acquiring some work experience in India). By contrast, individuals migrating for graduate school would typically do so right after their IIT degree. We suggest that the signaling value of having a Top 5 IIT degree may be less relevant for people who have work experience, since the work experience itself reveals important information, in particular for transfers within a firm.

[4] As we discuss later in Section 6, discussions on granting IIT status to BHU had been ongoing since the 1970s. Thus, while BHU becoming an IIT was a possibility, prospective students could not anticipate whether this change would have occurred by the time they graduated.

[5] Bockerman and Haapanen (2013) investigate the effect of a geographic expansion of higher education in Finland on internal mobility.

Bayona-Rodriguez, 2019). These effects tend to appear to be driven by signaling or networks, complementary to our findings regarding the attending an elite home country institution and migration.

The rest of the paper proceeds as follows. Section 2 provides historical background on the development of the IITs and details about the admissions process. Section 3 describes the data, followed by the empirical strategy in Section 4. Our main results are discussed in Section 5, followed by the potential mechanisms in Section 6. Section 7 concludes.

2. IITs: historical background and context

As India transitioned to independence after World War II, national leaders sought to establish higher education institutions focused on developing India's technological capacity. The institutions would conduct research in addition to teaching undergraduate and postgraduate students. Prominent IIT alumni include current CEO of Google and Alphabet Sundar Pichai, Sun Microsystems co-founder Vinod Khosla, and former IMF Chief Economist Raghuram Rajan.

The first of these higher technical institutions—called the Indian Institute of Technology—was founded in 1951 in Kharagpur. Over the following decade, another four IIT campuses opened: in Bombay (1958), Kanpur (1959), Madras (1959), and Delhi (1961). The five original IITs were spread across the country, each located in a different region.

The Institutes expanded in the late 1990s and early 2000s to include 23 branches (see Appendix Table A1). A few of the new branches—including IIT (BHU) Varanasi—were converted from existing institutions, which we will leverage in our analysis. We will refer to the five initial campuses as the "Top 5" IITs, as they have stronger reputations and rank higher than the newer institutes (for the locations of the Top 5 IITs, see Appendix Figure A1).[6]

At the undergraduate level, admissions to the IIT system are determined solely based on student performance on the annual Joint Entrance Examination (JEE), a centrally administered exam covering mathematics, chemistry, and physics. The competition is fierce; in 2010, for instance, around 450,000 individuals took the JEE, competing for less than 10,000 IIT places. Some IIT spots are reserved for special categories, including individuals from disadvantaged castes. We focus here on the general category where the majority of participants compete.

After the JEE results are released, test takers rank their top institution and major pairs (e.g., IIT Delhi/Electrical Engineering). Seats are then allocated by rank, with each student in turn "allotted" to their top still available institution-major seat.[7] The most popular combinations fill up quickly: IIT Bombay/Computer Science, for instance, only has around 40 seats available, and a rank of 100 in India would not be sufficient for admittance to that particular program (for opening and closing ranks for key institution/major combinations, see Appendix Table A2).

Instead of attending an IIT, test takers may attend a variety of other institutions, with the most popular options being the Birla Institute of Technology (BITS Pilani, ranked among the top 10 engineering colleges in India in2020[8]) and one of the National Institutes of Technology or NITs (see Appendix Table A3). Admission into the NITs is also based on the JEE examination.[9]

3. Data

Studying who migrates, empirically, is challenging since it requires information both about stayers and migrants. Few surveys have been conducted with a specific focus (or good coverage of) top talent.[10] To overcome the lack of relevant survey data, we use observational data generated by the unanticipated public posting of the results of the 2010 JEE online.,[11][12] The data released included full name and scores (math, chemistry, and physics). After receiving their JEE results, students enter the "allotment process" by which they are matched to institutions and major according to their preferences, rank, and available seats. We observe the result of this allotment process in the released JEE data, which in turn gives a good indication of where individuals studied for their undergraduate degree.[13] To complement the released JEE data, we systemically collected data on migration outcomes through an intensive manual data collection effort. Given the costs involved in the data collection, we focused on test takers from the very top (scoring 243 and above, corresponding to roughly the top 2500 scorers in the general category). Summary statistics of individuals are shown in Table 1. Appendix Figure A2 shows the distribution of total scorers for whom we manually collected outcomes. Individuals in this range would have the option to attend a Top 5 IIT in their choice set. Our final sample includes 2470 test takers. The data collection team used various sources to locate outcomes for individuals, including LinkedIn profiles, College alumni yearbooks, Github, AngelList, ResearchGate, and other sources. In searching for individuals, we leveraged the fact that we know not only their names but also the undergraduate institution they attended, and when they finished high school. We were able to find career and education histories (and thus directly infer migration information) for close to 90% of the sample. For the remainder, we assume that they have not migrated. We believe that this is a reasonable assumption given the widespread prevalence of LinkedIn in the U.S. (the main migration destination among identified migrants) and the sectors in which IIT

[6] "QS India University Rankings 2020." https://www.topuniversities.com/university-rankings/rankings-by-location/india/2020, accessed May 16, 2023.

[7] Test takers indicate their preferences for particular IIT/course combinations after finding out their own scores, while also knowing the likely cut-offs for entering particular IIT/course combinations. Therefore, strategic behaviour in choosing particular IIT/course combinations is not a major issue, unlike in the case of similarly selective exams where preferences are indicated in advance of taking the exam.

[8] India Today. "List of Top Engineering Colleges (2020) in India." https://www.indiatoday.in/bestcolleges/2020/ranks/1824927, accessed August 22, 2021.

[9] Careers360. "How to Get a Seat in NIT?" April 30, 2020. https://engineering.careers360.com/articles/how-get-seat-in-nit, accessed August 22, 2021.

[10] One exception is Agarwal et al. (2023), who survey around 500 former participants in the International Mathematical Olympiads, with a focus on the decision to migrate for undergraduate studies.

[11] Abhay Rana, a programmer also known as Nemo, found a way to scrape the JEE 2010 results and released them at https://captnemo.in/projects/iitjee/. Previously, the results of the JEE 2009 had been released in bulk format on the IIT-JEE website. Both the JEE 2010 and JEE 2009 data include names and scores, but the JEE 2010 data also includes the allotted institution and course.

[12] The use in research of potentially confidential data made publicly available through third parties is potentially controversial. A recent example of such use is Alstadsæter et al. (2019), who combine the "Panama papers" with administrative wealth records in Scandinavia to study tax evasion. Relatedly, Braguinsky et al. (2010) and Braguinsky and Mityakov (2015) use leaked administrative income data on Moscow citizens to shed light on issues of transparency and hidden earnings. In contrast to these studies, the data we use is rather less sensitive and confidential. Indeed, every year the names and scores of the top JEE scorers tend to be publicized by both coaching and testing centers. Moreover, following a freedom of information request, the Indian government released the full results of the 2009 JEE exams through the IIT-JEE website. The data released included information on names, names of the parents, scores, and locality for more than 400,000 individuals. The data we use is considerably smaller and generally has less information, but has the advantage of including the IIT and major individuals have chosen.

[13] In a few cases, students may not actually attend the institution to which they have been allotted. We checked the incidence of that and it seems to concern only a handful of cases. Moreover, there are few individuals (less than 1% of the sample) whose allotment status is missing; those are excluded from the analysis.

Table 1
Summary statistics.

	Mean	Std. Dev.
Top 5 IIT	0.732	0.443
Migrated	0.343	0.475
Migrated Grad School	0.251	0.433
Migrated Work	0.092	0.289
Migrated PhD	0.086	0.281
Migrated Master	0.164	0.371
Female	0.153	0.360
Score	277.33	29.590
Major		
Electrical Engineering	0.213	0.401
Computer Science	0.157	0.364
Mechanical Engineering	0.147	0.254
Civil Engineering	0.131	0.337
Chemical Engineering	0.124	0.329
Material Science	0.058	0.233
Aerospace Engineering	0.038	0.190
Physics	0.034	0.180
Observations	2470	

Notes: We present mean and standard variations for various variables in our main sample.

graduates tend to work. For instance, in 2022, LinkedIn was reported to have 175 million U.S. users, compared to a U.S. working-age population of 205 million. In the results section, we conduct sensitivity checks to alternative assumptions on the migration status of individuals with missing career histories.

We additionally collected outcomes for scorers lower in the score distribution, in ranks 5000 to 8,291, corresponding to scores of 197–220. However, we were only able to find migration outcomes for 68% of individuals in this sample. Individuals in this range (ranks 5000 to 8291) would have the option to attend a less prestigious IIT, but not one of the Top 5 IITs. Given the lower quality of this data, we only use it descriptively, to assess the share of migrants by score and rank (as in Fig. 1), but not in the main analysis.

4. Empirical strategy

Our empirical analysis compares migration outcomes of individuals who had the same score in the Joint Entrance Exam governing entry to the Indian Institutes of Technology. By comparing individuals with the same score, we control not just for ability (or prior stock of human capital) but also for the choice set faced by individuals. Indeed, a key advantage of our setting is that admissions are offered purely on the score in the Joint Entrance Exam and do not factor in unobservables such as essay quality, as would be the case in the U.S. context (Dale and Krueger, 2002; Arcidiacono et al., 2020).

In our main analysis, we run the following regression at the individual level:

$$Migrated_{ij} = \alpha + \beta_1 Top5IIT_i + \beta_2 \boldsymbol{X}_{ij} + \sum_j \mathbf{1}(Score)_j + \varepsilon_{ij} \tag{1}$$

Where i indexes individual exam takers and j exam scores (sum of mathematics, chemistry, and physics scores), with j being the score obtained by individual i. $Migrated_{ij}$ is an indicator variable for whether the individual migrated out of India after graduation (in some specifications, we distinguish whether the individual migrated for graduate school—Ph. D. or Masters—or migrated for work). $Top5IIT_i$ is an indicator variable for attending one of the five original IITs (IIT Bombay, IIT Kanpur, IIT Kharagpur, IIT Madras, and IIT Delhi). Technically, we observe which IIT individuals are "allotted" to attend, but this matches very closely with the institution individuals actually attend in our sample.

$\sum_j \mathbf{1}(Score)_j$ is a set of score fixed effects and $\boldsymbol{X}_{ij}$ is a vector of individual characteristics, including gender and major. By including score fixed effects, we compare equally talented students who scored high enough to study in a Top 5 IIT but chose not to attend.

As discussed earlier, selection by colleges is based on a student's entrance exam score, and we can control for scores directly in our regressions. However, there could be endogenous enrollment decisions in this setting or self-selection into IIT attendance, for instance, if individuals who are more motivated to migrate are also more likely to attend a Top 5 IIT. If so, our analysis would overstate the causal effect of attending a Top 5 IIT on migration.

A regression discontinuity research design based on scores in the Joint Entrance Exam would alleviate such concerns most effectively. However, there are no clear thresholds in JEE score that would lead to a large jump in IIT attendance, which prevents us from estimating the impact on the marginal attendee. For instance, as shown in Appendix Figure A3, the minimum rank that allows entry into a Top 5 IIT is 6,653, yet the share of scorers just above this rank going to a Top 5 IIT is quite low. The reason is that a score in this range would only suffice for an unpopular major at a Top 5 IIT (e.g., architecture rather than computer science) and that other IITs or engineering colleges are effectively more appealing. Similar issues apply to other plausible thresholds.[14]

5. Association of test scores with migration and IIT attendance

5.1. Migration

We first document that a large share of JEE test-takers eventually migrate abroad and, more generally, that the incidence is very high at the extreme right tail of the distribution. Fig. 1 shows the share of migrants across the score distribution and the share migrating for graduate school. Among the top 10 scorers, nine have migrated. Among the top 100 scorers, 62% have migrated, and 36% among the top 1000. While the incidence of migration is sizeable throughout our sample, it is striking that it increases dramatically towards the extreme right tail of the score distribution. To put things in perspective, more than 20 million people were born in India in 1992 and reached age 18 in 2010. Thus, the top 1000 scorers corresponds to 0.2% of the test takers and to 0.00005% of the birth cohort.

The U.S. is the main destination country, with 65% of the migrants heading to the US, 3% to Canada, 5% to the UK, and 16% to other countries (see Appendix Figure A4). Regarding the type of migration, as evident from Fig. 1, most individuals are migrating for graduate school. In our sample, 83% of individuals migrated to pursue a Master's or Ph.D. degree, with only 17% migrating for work. Among the top 10 scorers, only four migrated for graduate school and the others to work. The dominant type of migration in our sample is thus migrants going to graduate school in the United States. Naturally, these migrants may subsequently work in the U.S., but they first come to the U.S. as students.

5.2. Determinants of top 5 IIT attendance

A key concern in estimating the relationship between attending a Top 5 IIT and migration is the role of selection or endogenous enrollment decisions. As discussed earlier, attendance is determined solely by performance on the JEE exam, which also gives us a measure of ability that we can control for. However, there could be concerns about endogenous enrollment if certain individuals choose to attend a Top 5, and observed or unobserved factors are correlated with our outcome of interest (migration). While we cannot determine to what extent selection on unobservables plays, we next examine the determinants of Top 5 IIT attendance focusing on the observable characteristics we have in our

[14] In a study of affirmative action and the returns to attending engineering colleges in one Indian state, Bertrand et al. (2010) note that a regression discontinuity approach was not possible due to the strenuous data requirements. Data requirements also prevent us from implementing an IV strategy *à la* Kirkeboen, Leuven, and Mogstad (2016), who study returns to studying different majors using rich Norwegian administrative data.

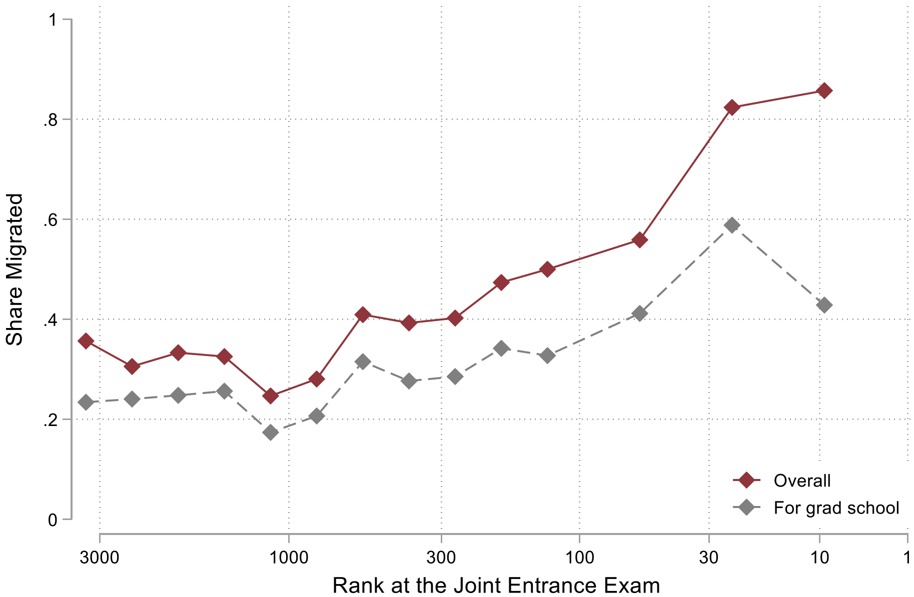


Fig. 1. Share Migrated by Rank
Notes: Admission to the Indian Institutes of Technology is exclusively through the Joint Entrance Exam (JEE). Our data leverages the unanticipated public release of the 2010 JEE data, combined with an intensive data collection effort on migration outcomes conducted by a dedicated team. This figure displays the share of 2010 JEE exam takers who migrated by 2018, among exam takers in the general category. The horizontal axis is the rank at the JEE (All India Rank).

data about test takers: gender and geography. Prior work shows that having to travel further to school or college is associated with higher costs, and distance to a school or college is used as an instrument for educational attainment (e.g., Card, 1995). Research has also suggested that women may differentially respond to the increased costs of traveling to a college further away from home. Borker (2021), for example, shows that in Delhi, women are willing to attend a lower quality college if the travel route is perceived to be unsafe.

Thus, gender and geography are important determinants of college attendance in some settings, but it is unclear whether they will play a similar role in this sample of top talent aiming to attend elite institutions. Next, we investigate whether gender and geography are significant determinants of attending a Top 5 IIT. Fig. 2 shows the share of test takers attending a Top 5 IIT by rank and gender (in 200-person bins). We can see that for the top 800-ranked test takers, while all women choose to attend a Top 5, and a small share of men do not attend a Top 5 in this part of the distribution, there do not seem to be large gender differences in the expected direction of women being less likely to attend a Top 5. After 1,000, the share attending a Top 5 falls, and there are no clear patterns in differences by gender. We note that Fig. 2 also shows clearly that at the top of the distribution, almost all test takers go to an IIT, which means that in this sample, almost no one is going to study in the U.S. instead of attending an IIT.[15]

In Table 2, we estimate the determinants of attending a Top 5 IIT. In column 1, we see that scoring higher on the JEE is significantly associated with attending a Top 5, which is expected as the sole criterion for admission to an IIT is score on the JEE. In column 2, we see that there is a negative relationship between being from a state with a Top 5 IIT located in it and attending a Top 5 IIT.[16] As evident in Figure A1 showing the location of the IITs, the Top 5 are indeed in ‘all corners’ of India, so geography may not play the driving force it might in other settings. In Column 3, we interact gender and state with a Top 5 IIT and find no significant gender differences in the role of geography. While we cannot account for the role of unobserved factors playing a role in attending a Top 5 IIT, this analysis suggests that scores are indeed the biggest determinant of attending a Top 5. We will explore the robustness of our main results to concerns about geography further in the next section.

6. Association of IIT attendance with migration, conditional on test scores

Now we turn to our analysis of the relationship between attending a Top 5 IIT and subsequent migration. In Table 3, we present regression results for attending a Top 5 IIT and migration based on our main sample of 2470 top scorers who had scores high enough to enter at least one track in a Top 5 IIT. As discussed in the empirical strategy section, we hold ability/prior human capital and the choice set constant by controlling for the number of points scored through fixed effects. Column 1 shows that attending a Top 5 IIT is associated with a 4.2 percentage point increase in the likelihood of migration. When we consider migration for graduate school specifically (column 2), we see that attending a Top 5 IIT is associated with a 4.9 percentage point increase in the propensity to migrate for graduate school and a 5.4 percentage point increase in the propensity to migrate for Ph.D. studies. Relative to the propensity among those not attending a Top 5 IIT (4.2%), this implies that going to a Top 5 IIT is associated with a higher likelihood of migrating for graduate school of over 100%. When we further separate migration for graduate school into migrating for a Ph.D. vs. a Master’s, most of the increase in the likelihood of migrating is for Ph.D. programs (almost 18 percentage points). Meanwhile, we see no significant effect for the likelihood of migrating for work (as opposed to for graduate school).

As discussed earlier, a key concern with the regressions in Table 3 is endogenous enrollment decisions. One way that endogenous enrollment can impact the estimates is if among two equally scoring individuals, one who has more family responsibilities or who has a strong attachment to the home region chooses to stay close to home and not attend a Top 5IIT. This would be a problem for our main estimates as these individuals would also be less likely to move abroad, biasing our estimates for attending a Top 5 on migration upwards.

To probe the extent to which our results from the main specification may be driven by individuals who are geographically bound to their home location, we run the regressions from above, excluding individuals

[15] This is consistent with accounts that it is highly competitive for the very top to go to an IIT and those with *lower* scores might go to the U.S. instead (Najar, 2011).

[16] While this may seem surprising, we note that because the Top 5 IITs are located in or nearby major population centers, students from a state with a Top 5 IIT may also have more attractive alternative education options nearby. For instance, students from the capital territory of Delhi are close to IIT Delhi (a Top 5 IIT) but also to IIT Roorkee (200 km away from Delhi). Because popular majors have lower entry requirements outside the Top 5 IITs, students may eschew more prestigious (and possibly closer) institutions for a more desirable major at a lower ranked institution.

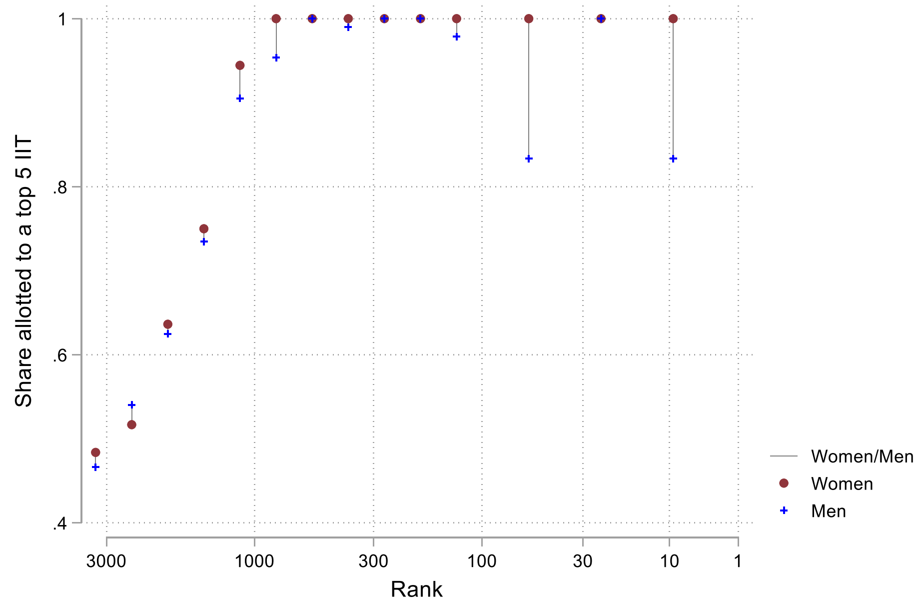


Fig. 2. Share of Test Takers Attending a Top 5 IIT by Rank and Gender
Notes: Admission to the Indian Institutes of Technology is exclusively through the Joint Entrance Exam (JEE). The horizontal axis is the rank at the JEE (All India Rank).

Table 2
Determinants of top 5 IIT attendance.

	(1)	(2)	(3)	(4)	(5)
Points at JEE Exam	0.006** (0.000)			0.006** (0.000)	0.006** (0.000)
From a State That Has a Top 5 IIT		−0.066** (0.019)	−0.066** (0.021)	−0.047** (0.017)	−0.049** (0.019)
Female			−0.001 (0.029)		0.000 (0.027)
Female X From a State That Has a Top 5 IIT			−0.002 (0.054)		0.013 (0.050)
Obs.	2470	2470	2470	2470	2470
Mean of DV	0.732	0.732	0.732	0.732	0.732
R2	0.157	0.005	0.005	0.159	0.159

Notes: This Table investigates observable determinants of studying in a Top 5 IIT. In all three specifications, we run a linear probability model with attending a Top 5 as the dependent variable. Robust Standard Errors in parentheses. + $p < 0.10$, *$p < 0.05$, **$p < 0.01$.

who study close to home.[17] First, we note that the share of students studying close to home is small: 86% of students study outside their home states and 82% study more than 200 km away. In Table 4, Panel A, where we exclude those who study in the same state, the results are quite similar across all outcomes to the main specification. In Table 4, Panel B, where we exclude those who study more than 200 km away, only the main effect of migrating for a Ph.D. holds, but the point estimates for the other outcomes are similar. Overall, this evidence provides some reassurance that the results are not driven by pre-existing (and persistent) geographical mobility constraints.

A separate concern relates to the fact that we impute migration status to non-migrant for individuals in our sample who have missing career histories (11 percent of the sample). In Appendix Table A4, we report the result of a sensitivity exercise where we assume instead that all individuals with missing career histories are migrants. The results are similar to those of the main specification despite the very conservative assumption, possibly due to the fact that having a missing career history is not correlated with attending a Top 5 IIT (controlling for score).

[17] To code distance, we exploit the fact that we can observe in which testing centers (out of 300+) individuals took the JEE test. Taking the testing center as a proxy for home location, we compute the distance between the home location and the college attended.

7. Potential mechanisms

7.1. Human capital: choice of major

One potential explanation for the estimates in Table 3 is differences in the human capital obtained by those attending Top 5 IITs. One way human capital can differ is if the quality of education differs across Top 5 IITs and other institutions attended by individuals in our sample. While we cannot directly test for differences in the quality of education, the Top 5 IITs and other IITs and non-IIT engineering colleges are known to provide high-quality instruction. Another way human capital could differ is if those who attend a Top 5 IIT pursue different courses of study or majors. As discussed in section 2, admission to a particular IIT is course-specific, so individuals are choosing an institution and a course of study simultaneously. Individuals in our sample commonly face a choice between pursuing a more popular major (such as computer science) outside a Top 5 engineering college or a less popular major in a Top 5 IIT.

We indeed find that those who attend a Top 5 IIT pursue different majors than individuals not attending an IIT. In Appendix Table A5, we show that controlling for the total score, those who attend a Top 5 IIT are less likely to complete a computer science, electrical engineering, or mechanical engineering major. However, once we control for major area of study in our main regression estimating the impact of Top 5 IIT on migration (shown in Table 5), we find similar results as in Table 2. This

Table 3
Attending a top 5 IIT and migration.

	Migrated	Migrated Grad	Migrated Work	Migrated PhD	Migrated Master
	(1)	(2)	(3)	(4)	(5)
Attended a Top 5 IIT	0.042^{+} (0.024)	0.049* (0.022)	−0.007 (0.015)	0.053** (0.013)	−0.004 (0.020)
Female	0.033 (0.028)	0.041 (0.026)	−0.007 (0.016)	0.033^{+} (0.018)	0.007 (0.022)
Points FE	Yes	Yes	Yes	Yes	Yes
Obs.	2470	2470	2470	2470	2470
Mean of DV for Individuals Not Going to a Top 5 IIT	0.305	0.211	0.094	0.042	0.167
Share Going to a Top 5 IIT	0.725	0.725	0.725	0.725	0.725
R2	0.086	0.088	0.093	0.096	0.081

Notes: Admission to the Indian Institutes of Technology is exclusively through the Joint Entrance Exam (JEE). Our data leverages the unanticipated public release of the 2010 JEE data combined with an intensive data collection effort on migration outcomes conducted by a dedicated team. Our dependent variable is whether the individual migrated from India (column 1), whether the individual migrated from India to attend graduate school (Master's or Ph.D., column 2), whether the individual migrated from India to attend graduate school for a Master's degree (column 4), whether the individual migrated from India to attend graduate school for a Ph.D. degree (column 5) or whether the individual migrated from India for work (column 3). The sample includes the 2470 top scorers in the general category (scores 243 and above, corresponding to an All India Rank below 3000). Estimation is by OLS. We control for JEE score fixed effects (and hence ability/prior human capital, as well as the choice set faced by individuals). Robust standard errors in parentheses. $+p < 0.10$, $*p < 0.05$, $**p < 0.01$.

Table 4
Attending a top 5 IIT and migration: Excluding individuals studying near home.

Panel A: Exclude individuals studying in the same state	Migrated	Migrated grad	Migrated work	Migrated PhD	Migrated Master
	(1)	(2)	(3)	(4)	(5)
Attended a Top 5 IIT	0.048^{+} (0.026)	0.053* (0.024)	−0.005 (0.016)	0.056** (0.014)	−0.003 (0.021)
Observations	2133	2133	2133	2133	2133
R2	0.095	0.094	0.098	0.107	0.093
Panel B: Exclude individuals studying less than 200 km away	Migrated (1)	Migrated grad (2)	Migrated work (3)	Migrated PhD (4)	Migrated Master (5)
Attended a Top 5 IIT	0.030 (0.028)	0.033 (0.025)	−0.003 (0.017)	0.048** (0.015)	−0.015 (0.022)
Observations	2031	2031	2031	2031	2031
R2	0.093	0.093	0.104	0.107	0.091

Notes: Individuals who forego studying at a Top 5 IIT may do so to stay closer to family (say to take care of an ailing parent or younger sibling) or because they have a strong attachment to their home region. This, in turn, could lead to lower migration propensities. This table investigates the robustness of our results to excluding individuals who study close to home and may thus be "geographically bound." Panel A replicates Table 3, panel B is run on the subsample of individuals who study outside their home state, and panel C is run on the subsample of individuals who study outside a 200 km radius from the location where they took the JEE test. All specifications include JEE score fixed effects and gender. Robust standard errors in parentheses. $+p < 0.10$, $*p < 0.05$, $**p < 0.01$.

Table 5
Controlling for major.

	Migrated	Migrated Grad	Migrated Work	Migrated PhD	Migrated Master
	(1)	(2)	(3)	(4)	(5)
Attended a Top 5 IIT	0.053^{+} (0.031)	0.036 (0.029)	0.016 (0.019)	0.039* (0.018)	−0.003 (0.025)
Female	0.031 (0.028)	0.038 (0.026)	−0.007 (0.016)	0.031^{+} (0.018)	0.007 (0.022)
Major:					
Computer	0.088^{+} (0.048)	−0.034 (0.044)	0.122** (0.030)	−0.013 (0.029)	−0.022 (0.038)
Electrical Eng.	−0.018 (0.045)	−0.023 (0.041)	0.005 (0.026)	0.003 (0.026)	−0.027 (0.036)
Mechanical Eng.	−0.026 (0.045)	−0.027 (0.043)	0.002 (0.024)	−0.006 (0.027)	−0.021 (0.037)
Chemical Eng.	0.017 (0.043)	−0.020 (0.040)	0.037 (0.025)	0.017 (0.026)	−0.037 (0.034)
Civil Eng.	−0.068 (0.043)	−0.066 (0.040)	−0.003 (0.023)	−0.016 (0.024)	−0.049 (0.035)
Material Science	−0.017 (0.052)	−0.034 (0.047)	0.016 (0.032)	−0.010 (0.028)	−0.024 (0.042)
Aerospace Eng.	0.011 (0.060)	0.007 (0.057)	0.004 (0.033)	0.100* (0.045)	−0.093* (0.044)
Physics	0.145* (0.066)	0.134* (0.064)	0.010 (0.034)	0.095* (0.047)	0.039 (0.055)
Points FE	Yes	Yes	Yes	Yes	Yes
Obs.	2470	2470	2470	2470	2470
Mean of DV. (Among those not going to a Top 5 IIT)	0.305	0.211	0.094	0.042	0.167
R2	0.096	0.094	0.110	0.105	0.084

Notes: This Table replicates Table 3 but also controls for major studied in undergraduate. Our dependent variable is whether the individual migrated from India (column 1), whether the individual migrated from India to attend graduate school (Master's or Ph.D., column 2), whether the individual migrated from India to attend graduate school for a Master's degree (column 4), whether the individual migrated from India to attend graduate school for a Ph.D. degree (column 5) or whether the individual migrated from India for work (column 3). Estimation is by OLS. We control for JEE points fixed effects. The omitted major category is miscellaneous major. Robust standard errors in parentheses. $+p < 0.10$, $*p < 0.05$, $**p < 0.01$.

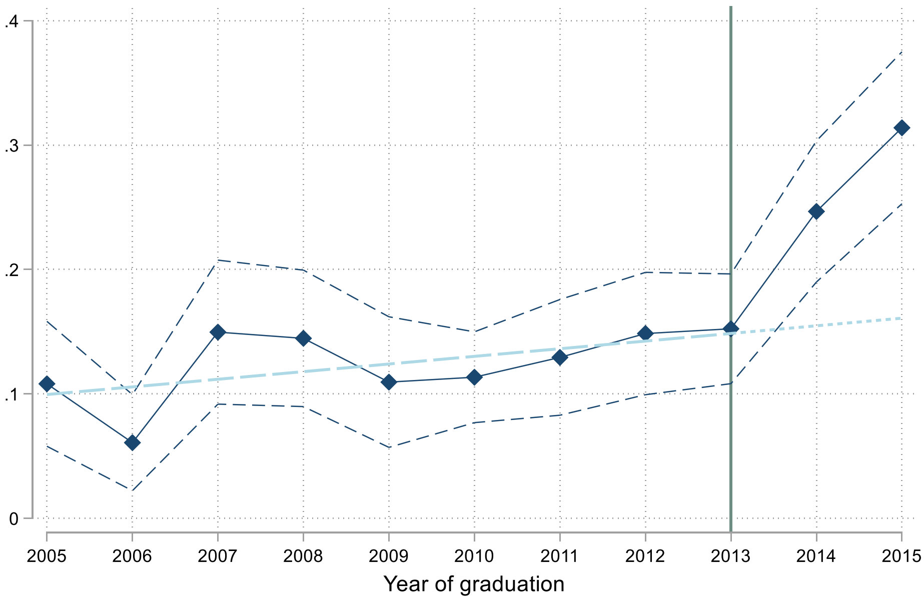


Fig. 3. Share of BHU Graduates Migrating Before and After BHU Acquired IIT Designation
Notes: The Figure displays the share of Banaras Hindu University (BHU) graduates migrating within five years of graduation, by year of graduation. In June 2012, the Institute of Technology at BHU became Indian Institute of Technology (BHU) Varanasi, without concomitant changes to its staffing or curriculum. The first cohort potentially affected would be the one graduating in 2013. Individuals graduating in 2014 (respectively 2015) would have enrolled in 2010 (respectively 2011), when it was not known if/when BHU would become an IIT (discussions about designating BHU as an IIT had been ongoing since the 1970s). Superimposed is a linear fit based on the years 2005–2013.

Table 6
IIT designation and migration among BHU graduates.

	Migrated		Migrated for Grad School	
	(1)	(2)	(3)	(4)
IIT Designation (Graduated in 2013, '14 or '15)	0.118** (0.019)	0.062* (0.028)	0.088** (0.018)	0.054* (0.026)
Year of Graduation (BHU)		0.011** (0.004)		0.007+ (0.004)
Obs.	1956	1956	1956	1956
Mean of DV (Pre-2013 Cohorts)	0.166	0.166	0.141	0.141
R2	0.030	0.033	0.026	0.027

Notes: This Table analyzes migration propensities among (BHU) graduates. In June 2012, the Institute of Technology at BHU became Indian Institute of Technology (BHU) Varanasi, without concomitant changes to its staffing or curriculum. The first cohort potentially affected would be the one graduating in 2013. Individuals graduating in 2013 (respectively 2014, 2015) would have enrolled in 2009 (respectively 2010, 2011), when it was not known if/when BHU would become an IIT (discussions about designating BHU as an IIT had been ongoing since the 1970s). The sample includes BHU graduates from 2005 to 2015 and we consider cohorts graduating in 2013, 2014, and 2015 as treated by IIT designation. The dependent variables are migrating out of India within five years of BHU graduation (column 1 and 2) or migrating out of Indian for graduate school within five years of BHU graduation (column 3 and 4). Columns 2 and 4 control for a linear time trend in the year of graduation. Estimation is OLS. Both specifications include major fixed effects. Robust standard errors in parentheses.$+p < 0.10$, $*p < 0.05$, $**p < 0.01$.

suggests that human capital differences in terms of major area of study are likely not playing a large role in the differences in migration probabilities. Appendix Table A6 also shows interactions of Top 5 and different majors on our main outcomes. There do not seem to be clear differences in the role of a Top 5 b y major. Further, course selectivity does not appear to be correlated with migration when controlling for Top 5 IIT attendance (shown in Appendix Table A7).

7.2. Signaling: the BHU name change

Next, we examine whether the IIT 'brand' may play a signaling role that facilitates migration. Distinguishing the signaling value of the IIT brand from other features of an IIT education is challenging. However, we are able to leverage an interesting situation whereby one university received IIT designation without any concomitant changes to its staff, curriculum, or admission system, similar to the approach used by studies of the signaling value of university names (Acton, 2022) or degrees (Tyler et al., 2000) net of human capital effects. We note that similar to Acton (2022), the signaling value of the IIT brand here does not imply signaling on students' innate ability, but rather that the IIT diploma may provide a signal of the quality of the human capital gained in an IIT to graduate schools or employers after graduation.

Institute of Technology at Banaras Hindu University, a respected engineering college tracing its roots to the early 20th century, became the Indian Institute of Technology (BHU) Varanasi in 2012.[18] The timing of the change was difficult to anticipate: the IIT Council initially proposed converting IT-BHU into an IIT campus as early as 1971, but political considerations led the proposal to be shelved for many years until it took effect in 2012.[19] While the name officially became IIT BHU on

[18] The institution was founded in 1919, as Banaras Engineering College (BENCO).

[19] IIT (BHU) Varanasi is one of three IIT locations that were converted from existing institutions. In August 2010, Minister of State for Human Resource Development D. Purandeswari introduced a bill formalizing the conversion, by amending the 1961 Institutes of Technology Act. The amendment passed the Lok Sabha (lower house of Indian parliament) in March 2011 and the Raiya Sabha (upper house of Indian parliament) in April 2012. It was signed into law by the President of India in June 2012.

Table 7
Determinants of U.S. PhD program among IIT computer science graduates.

Multinomial Logit Reporting Relative Risk Ratios	(1)	(2)	(3)
Alumni of own IIT among faculty of U.S. PhD program	1.294* (0.198)		1.295* (0.202)
Alumni of other IITs among faculty of U.S. PhD program		1.010 (0.072)	0.996 (0.076)
JEE Score	1.000 (0.005)	1.000 (0.005)	1.000 (0.005)
Observations	975	975	975
Individuals	39	39	39
Choices	25	25	25
Pseudo R2	0.01	0.000	0.01
Mean of dependent variable	0.04	0.04	0.04

Notes: For this analysis, we focus on computer science, where we are able to observe precisely the faculty composition of U.S. graduate programs. Our sample is based on the 39 individuals in our sample who enrolled in a U.S. Ph.D. program in computer science, and the top 25 computer graduate programs in the U.S. News of the World ranking as potential destinations. Our variables of interest are (1) the number of faculty members in the U.S. program who are alumni of the IIT attended by the student, and (2) the number of faculty members in the U.S. program who are alumni of other IITs. We estimate a multinomial logit choice model and report relative risk ratios. Standard errors in parentheses.

June 21, 2012, it took time for the name to be used practically. For example, the website only went live in late September 2012.[20]

Using a purpose-built ancillary dataset, we compare the migration rate of the BHU students graduating before and after it received the IIT designation. Note that the cohorts of students enrolled at BHU at the time of the change had made their decision to study at BHU without knowing when BHU might become an IIT. Since we are comparing migration rates across different cohorts, we define our outcome of interest to be migration within five years of graduation in order to avoid truncation issues.

The data for the BHU students was collected from the IIT BHU Alumni website and LinkedIn.[21] The sample of 1956 BHU students includes all students who graduated from BHU between 2005 and 2015 with a B. Tech, B. Pharm, M. Tech, or IDD degree.[22] In case of ambiguity in matching student names across the Alumni website dataset and LinkedIn, the team of RAs used information on the department of study at BHU and graduation year to determine the match.

Fig. 3 shows the share of students migrating (for graduate school) by year of graduation from 2005 to 2015. There is a slow secular increase in migration throughout the period (as shown through the linear trend). There is also a clear increase in the share migrating for graduate school for those who graduated in 2014 and 2015 after BHU became an IIT. Table 6 shows the regression estimates comparing the migration probability of students graduating in 2013–2015 vs. earlier years before the change to an IIT. This shows that controlling for a linear time trend, the designation of BHU as an IIT led to a 5.4 percentage point increase in the probability of migration for graduate school. Compared to a baseline propensity of 10.5 percent prior to IIT designation, our estimates correspond to a roughly 50 percent increase in the propensity to migrate for graduate school. While sizeable, this effect size is noticeably smaller than in the main specification of section 5. The difference could be due to Top 5 IITs providing a stronger signal, to the main specification estimates, or both.

One limitation of the preceding results is that they are based on time effects within BHU graduates. To provide some reassurance on the validity of the analysis, we also compare BHU graduates to graduates from two other engineering colleges that did not gain IIT designation in a simple difference-in-differences setting (shown in Appendix Table A8). The point estimate for the diff-in-diff coefficient is positive and significant, and larger in magnitude than in the main exercise. However, the diff-in-diff results are also noisy due to shorter time coverage and the relatively small number of students in the control institutes.

Taken as a whole, the results from this subsection suggest that the IIT brand by itself facilitates migration and that signaling may play a role in the greater incidence of migration among IIT graduates.

8. Role of alumni networks

Lastly, we examine whether alumni networks can facilitate migration. Alumni networks can lower the costs of migration for IIT students by providing information about educational and employment opportunities. Alumni may also facilitate access to particular programs where they have influence over admissions or hiring decisions.

To examine the role of networks, we consider the case of computer science graduate programs in the U.S., where we are able to precisely observe the composition and, importantly, the undergraduate education of faculty members, thanks to a community data collection effort (Papoutsaki et al., 2015). The computer science faculty data cover around 2400 faculty members in 55 top U.S. graduate programs. Remarkably, 134 (5.6%) of these faculty members are alumni of one of the IITs. The distribution of these IIT alumni is uneven, with 12 programs having no IIT alumni at all and MIT and the University of Illinois each having as many as eight.

We next combine the faculty data with information on which universities IIT graduates in our sample attended for their U.S. graduate studies. We focus here on the 39 individuals in our sample who enrolled in a U.S. graduate program in computer science and the top 25 graduate programs in the U.S. News of the World ranking.[23] For each individual, we consider the 25 potential destinations and estimate a multinomial logit model of the type:

[20] From the Way Back Machine the posting of the new website in September 2012 is evident: https://web.archive.org/web/20120915000000*/https://www.iitbhu.ac.in/.

[21] IIT BHU Alumni website can be accessed at: https://connect.iitbhuglobal.org/members.dz#.

[22] Including the following streams of study: Biochemical Engineering, Ceramic Engineering, Chemical Engineering, Civil Engineering, Computer Science Engineering, Electrical Engineering, Electronics Engineering, Mechanical Engineering, Metallurgical Engineering, Mining Engineering, Pharmaceutical Engineering, Material Science & Technology, Biomedical Engineering, Industrial Management, Power Electronics, Systems Engineering, and Power Systems.

[23] We are considering this particular—admittedly small—slice of our sample because we know the faculty composition of various U.S. departments in computer science, but not in other disciplines. We observe only a handful of IIT graduates enrolling in computer science program outside the top 25.

$$\log \frac{p(Y_{ij}=k)}{p(Y_{ij}=K)} = \alpha + \beta_1 Own\_IIT\_alumni_{ijk} + \beta_2 Other\_IIT\_alumni_{ijk} + \beta_3 Score_i + \varepsilon_{ijk}$$

where i indexes individuals, j indexes the IIT they are graduating from with an undergraduate degree, k indexes U.S. Ph.D. programs, and $Score_i$ is the score the individual obtained on the IIT Joint Entrance Exam. Our dependent variable is the log odds of enrolling in a particular program k. Our variables of interest are (1) $Own\_IIT\_alumni_{ijk}$—the number of faculty members in the U.S. program who are alumni of the IIT attended by the student—and (2) $Other\_IIT\_alumni_{ijk}$—the number of faculty members in the U.S. program who are alumni of other IITs. To illustrate, the computer science department at MIT has five alumni from IIT Madras among its faculty members, as well as one alumnus from IIT Bombay, one from IIT Delhi, and one from IIT Kanpur. A student from IIT Madras considering MIT would have a value of five for $Own\_IIT\_alumni_{ijk}$ and a value of three for $Other\_IIT\_alumni_{ijk}$.

Table 7 reports the results of the multinomial logistic model as relative risk ratios. An additional alumnus from one's own IIT in a particular destination is associated with a 30% increase in the likelihood of enrolling in that destination. By contrast, the number of IIT alumni from other IITs does not appear to correlate with the decision to enroll in a program: the point estimate of the relative risk ratio is not just insignificant, but is also very close to one. Overall, the results suggest that alumni networks may facilitate access to particular U.S. graduate programs.

9. Conclusion

Using a novel dataset of students taking the JEE exam and their education and career outcomes, we have documented that the incidence of migration among top talent is sizeable, and particularly so at the very right tail of the talent distribution. Among the top 1000 scorers at the JEE (corresponding to 0.2% of the test takers and 0.00005% of the birth cohort), the share of migrants is around 36%, rising to 62% among the top 100 scorers, and to 9 out of the top 10 scorers. While prior literature has documented that the incidence of migration rises with educational attainment (Saint-Paul, 2004; Docquier and Marfouk, 2006; Docquier and Rapoport, 2012; Grogger and Hanson, 2011; Kerr et al., 2016), our work reveals that this masks considerable heterogeneity among the tertiary-educated in the ability dimension. Indeed, the incidence of migration rises dramatically among the most extraordinarily able, as conjectured by Saint-Paul (2004).

We have also documented that graduates of the most elite IITs are more likely to migrate abroad after graduating compared to equally talented individuals who chose other IITs. Prior research has documented the large enrollment of Indian students in U.S. graduate programs (Bound et al., 2021). We show that Indian educational institutions are playing an important role in facilitating this enrollment, as Top 5 IIT graduates are more likely to migrate for graduate school than others, and to migrate to the U.S. to attend Ph.D. programs, in particular. We find that this is likely due to the signaling value of the IIT brand, as well as to the networks that are formed among alumni of specific IIT campuses. In fact, these networks likely play an even larger role than our analysis of computer science faculty alumni networks suggests.

While prior work has emphasized the gatekeeping role of elite universities in *host* countries (Kerr et al., 2016; Amornsiripanitch et al., 2021), our paper surfaces the similar role played by elite universities in *source* countries. While we cannot observe the full extent of the mechanisms contributing to these effects, our analysis suggests that through a combination of signaling and network effects, elite universities in source countries play a key role in shaping migration outcomes, both in terms of the overall propensity and the particular migration destination. We note that the fact that elite home universities act as gatekeepers for migration further raises the stakes of their own admission policies.

We conclude by mentioning two lines of inquiry that could be explored in future research. The first is why the incidence of migration rises dramatically at the very right tail of the talent distribution (above and beyond the gatekeeping role of universities). One potential explanation is that the private return to extraordinary ability is higher in destination countries (perhaps due to agglomeration effects) than in source countries. This raises the question of whether home countries should make special efforts to retain their top talent. It will be interesting to study whether patterns of migration at the right tail of the talent distribution change based on increased access to entrepreneurial opportunities in the home country,[24] adoption of remote work, or other contemporary changes. The second avenue to explore is whether alternative arrangements to the current dominant skilled migration model (with elite universities in home and host countries acting as gatekeepers) would be preferable from the point of view of the source country, destination country, or the immigrants themselves. For instance, analysis could examine the impacts of the United Kingdom's new "High Potential Individual" visa route, open to graduates from the top 50 global universities, to attract global talent.[25] Other scenarios to examine in further research include whether IIT graduates could be hired by U.S. companies straight out of their undergraduate programs (instead of obtaining graduate degrees in the U.S.) or whether U.S. universities should formally use JEE scores in their undergraduate admission decisions or give scholarships to attract top talent to their institutions.

Author statement

All authors contributed equally to the paper.

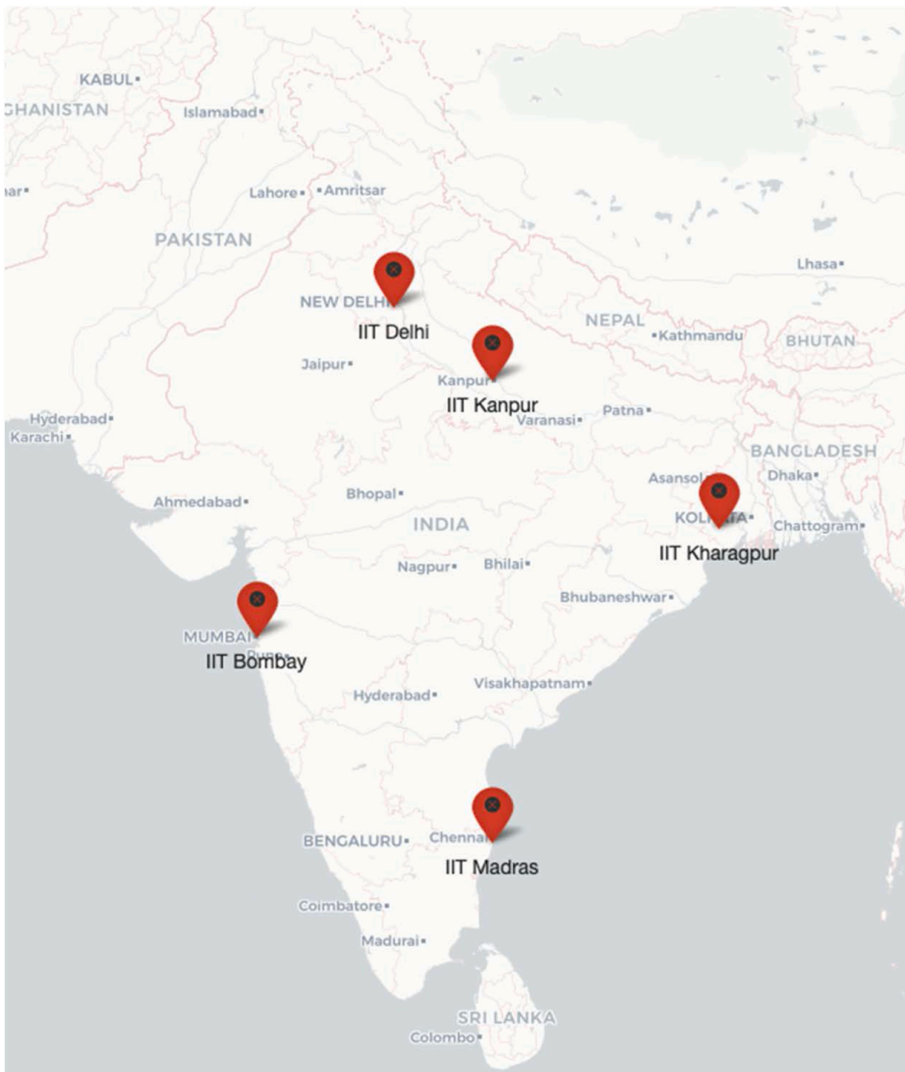
Data availability

Data will be made available on request.

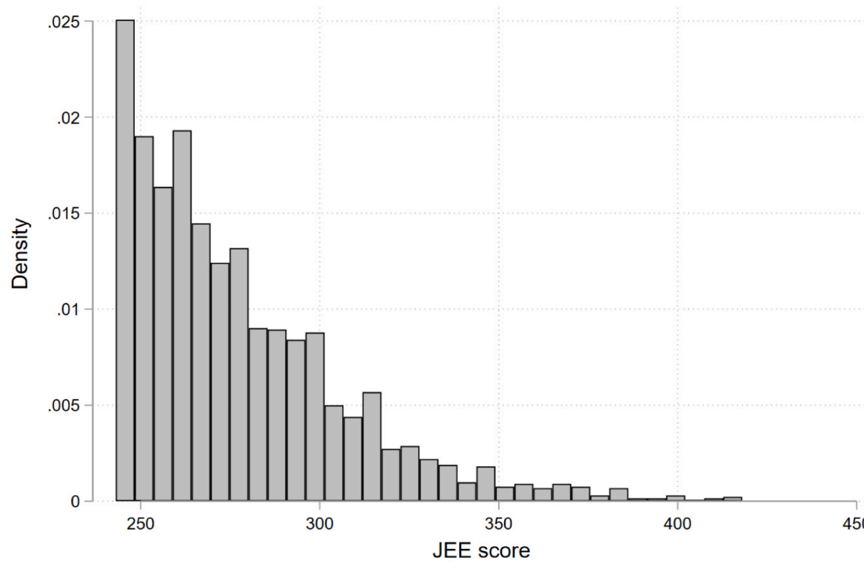
[24] An example of such increased access to entrepreneurship opportunities relates to the relatively recent founding of research parks at some of the IITs. See: https://respark.iitm.ac.in/.

[25] As of 2022, however, this list did not include any IITs, or indeed any Indian university.

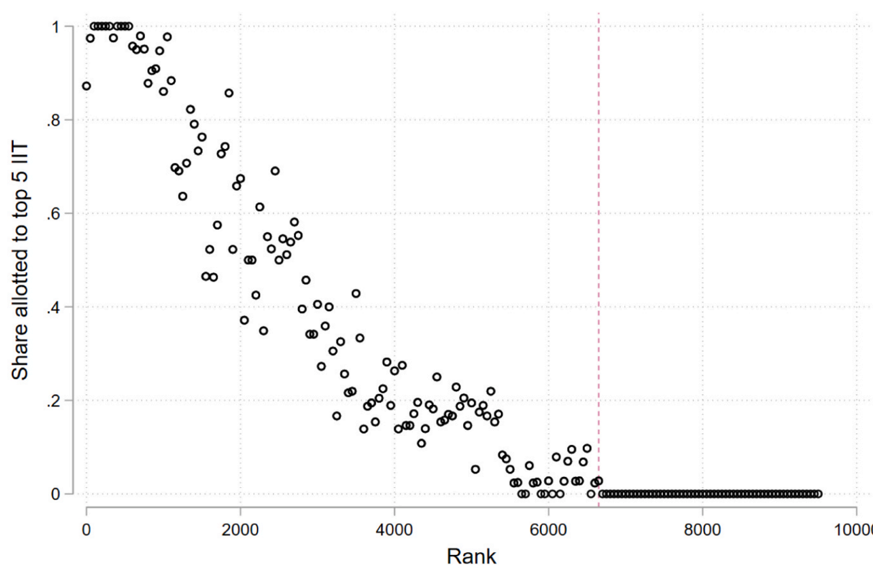
Appendix



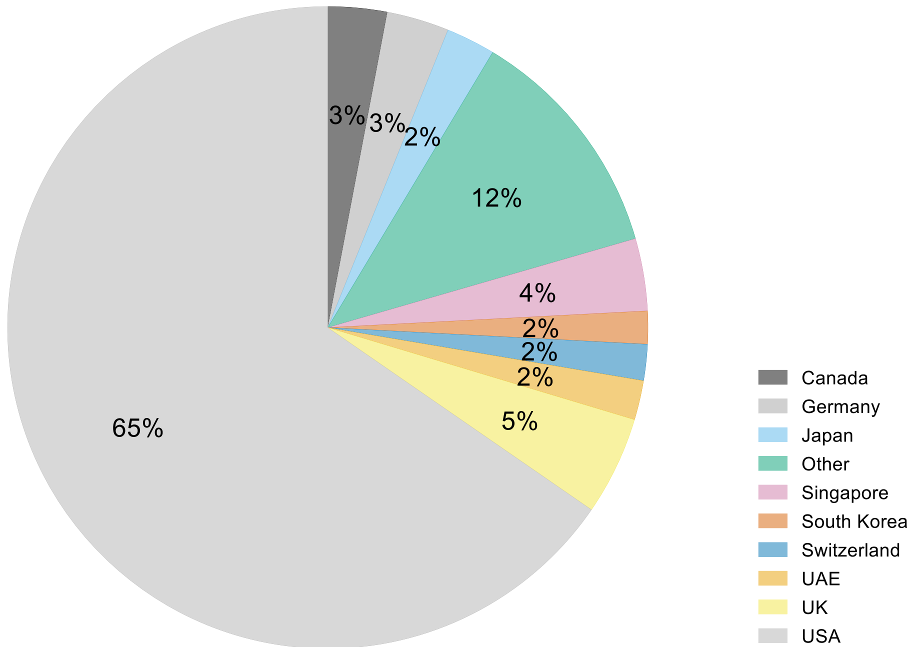
Appendix Fig. A1. Location of Top 5 IITs in India. *Notes*: The Figure displays the location of the original "Top 5" IITs. For a complete list of the IITs and their date of establishment, see Appendix Table A1.



Appendix Fig. A2. Distribution of JEE Scores in Main Sample. *Notes:* This Figure shows the distribution of total scores (sum of mathematics, chemistry, and physics scores) in the sample for which we manually collected outcomes. N = 2470.



Appendix Fig. A3. Share of JEE Test Takers Allotted to a Top 5 IIT by Rank. *Notes:* This Figure displays the share of JEE test takers allotted to a top 5 IIT by their rank in the JEE (in bins of 50 individuals).



Appendix Fig. A4. Destinations of Migrants. *Notes:* This Figure shows the first migration destination country for individuals in our main sample. N = 2470.

Appendix Table A1
Location and Establishment Date of IIT Institutions

Institution Name	Established	State
IIT Kharagpur	1951	West Bengal
IIT Bombay	1958	Maharashtra
IIT Kanpur	1959	Uttar Pradesh
IIT Madras	1959	Tamil Nadu
IIT Delhi	1961	Delhi
IIT Guwahati	1994	Assam
IIT Roorkee	2001*	Uttarakhand
IIT Bhubaneswar	2008	Odisha
IIT Gandhinagar	2008	Gujarat
IIT Hyderabad	2008	Telangana
IIT Jodhpur	2008	Rajasthan
IIT Patna	2008	Bihar
IIT Ropar	2008	Punjab
IIT Indore	2009	Madhya Pradesh
IIT Mandi	2009	Himachal Pradesh
IIT (BHU) Varanasi	2012**	Uttar Pradesh
IIT Palakkad	2015	Kerala
IIT Tirupati	2015	Andhra Pradesh
IIT (ISM) Dhanbad	2016ˆ	Jharkhand
IIT Bhilai	2016	Chhattisgarh
IIT Dharwad	2016	Karnataka
IIT Goa	2016	Goa
IIT Jammu	2016	Jammu and Kashmir

Notes: *IIT Roorkee was established by bringing the University of Roorkee (previously Thomason College of Engineering), founded in 1847, into the IIT system. **IIT (BHU) Varanasi was established by bringing the Institute of Technology at Banaras Hindu University (IT-BHU), founded in 1919, into the IIT system by the Institutes of Technology (Amendment) Act of 2012. ˆIIT (ISM) Dhanbad was established by bringing the Indian School of Mines (ISM), founded in 1926, into the IIT system.
Sources: Our Heritage. (n.d.). Indian Institute of Technology Roorkee. https://www.iitr.ac.in/institute/ pages/Heritage.html, accessed October 14, 2020; The National Institutes of Technology (Amendment) Act of 2012, No. 28 (2012). https://www.mhrd.gov.in/sites/upload_files/mhrd/files/upload_document/ NIIT_Notification_08062012.pdf; *History and Discovery*. (n.d.). Indian Institute of Technology (ISM) Dhanbad. https://www.iitism.ac.in/index.php/pages/about_history, accessed October 14, 2020.

Appendix Table A2
General List Opening/Closing Ranks for Select IIT Locations/Programs, 2010

	Chemical Engineering	Civil Engineering	Computer Science	Electrical Engineering	Mechanical Engineering
Bombay	512–872	887–1474	2–116	1–98	56–471
Delhi	736–1038	717–1553	3–124	76–252	249–603
Kanpur	851–1372	1010–1910	39–231	148–467	531–772
Kharagpur	1413–1949	1842–2317	268–644	783–991	787–1156
Madras	561–1797	1325–2120	7–232	109–338	310–777
BHU Varanasi	3385–4355	3317–4309	1558–2696	1720–3285	2519–3573

Appendix Table A3
Colleges Attended for Top Scorers (279 and Above) Not Attending a Top 5 IIT

Bachelor's College	Frequency	Percent
IIT Roorkee	295	43.0%
IIT Guhawati	187	27.2%
BHU Varanasi	78	11.3%
IIT Hyderabad	53	7.7%
IIT Gandhinagar	46	7.0%
Other IIT Institutions	27	3.8%
Total	686	100%

Appendix Table A4
Attending a Top 5 IIT and Migration: Robustness to Different Treatment of Observations with Missing Career History

	Migrated	Migrated Grad	Migrated Work	Migrated PhD	Migrated Master
	(1)	(2)	(3)	(4)	(5)
Attended a Top 5 IIT	0.038 (0.026)	0.048^{+} (0.025)	−0.011 (0.018)	0.054** (0.016)	−0.005 (0.023)
Female	0.073* (0.029)	0.070* (0.028)	0.003 (0.018)	0.045* (0.020)	0.024 (0.024)
Points FE	Yes	Yes	Yes	Yes	Yes
Obs.	2470	2470	2470	2470	2470
Mean of DV for Individuals Not Going to a Top 5 IIT	0.461	0.326	0.134	0.077	0.249
Share Going to a Top 5 IIT	0.725	0.725	0.725	0.725	0.725
R2	0.085	0.084	0.079	0.079	0.079

Notes: As discussed in the main text, career histories could not be traced for around 11% of individuals in the sample. We generally assume these individuals have not migrated. In this robustness table, we reproduce Table 3 assuming these individuals *did* migrate (in terms of type of migration—migrating for work/graduate school/Ph.D./Master's—we assume each type occurs in the same proportion as in the observed migration episodes). Note that share of observation with missing career histories is similar across those who attended a Top 5 or not. Robust standard errors in parentheses. $+ p < 0.10$, $*p < 0.05$, $**p < 0.01$.

Appendix Table A5
Do Top IIT Attendees Have Different Majors?

Major	Comp. Science	Elect. Eng.	Mech. Eng.	Chem. Eng.	Civil. Eng.	MaterialScience	Aerospace Eng.	Physics
Attending a Top 5 IIT	−0.228** (0.019)	−0.306** (0.020)	−0.109** (0.015)	0.090** (0.016)	0.082** (0.018)	0.164** (0.014)	0.079** (0.009)	0.049** (0.008)
Female	−0.003 (0.019)	0.046* (0.022)	−0.019 (0.019)	−0.004 (0.018)	−0.000 (0.019)	−0.005 (0.013)	0.005 (0.012)	0.018 (0.011)
N	2470	2470	2470	2470	2470	2470	2470	2470
Mean of DV (Among Those Not Going to a Top 5 IIT)								
R2	0.257	0.253	0.178	0.101	0.142	0.167	0.078	0.070

Notes: The dependent variable is a dummy variable for each major indicated. Estimation is by OLS. We control for gender and JEE score fixed effects. Standard errors in parentheses.$+p < 0.10$, $*p < 0.05$, $**p < 0.01$.

Appendix Table A6
Interacting Top 5 IIT with Major

	Migrated	Migrated Grad	Migrated Work	Migrated PhD	Migrated Master
	(1)	(2)	(3)	(4)	(5)
Top 5 × Computer Science	0.017 (0.062)	0.029 (0.053)	−0.011 (0.046)	0.036 (0.036)	−0.007 (0.045)
Top 5 × Electrical Eng.	0.030 (0.054)	0.018 (0.049)	0.011 (0.031)	0.021 (0.033)	−0.002 (0.042)

(*continued on next page*)

Appendix Table A6 (*continued*)

	Migrated	Migrated Grad	Migrated Work	Migrated PhD	Migrated Master
	(1)	(2)	(3)	(4)	(5)
Top 5 × Mechanical Eng.	0.034 (0.063)	0.031 (0.059)	0.003 (0.033)	0.004 (0.035)	0.027 (0.051)
Top 5 × Chemical Eng	0.090 (0.071)	0.061 (0.065)	0.028 (0.047)	0.071^{+} (0.038)	−0.009 (0.057)
Top 5 × Civil Eng.	0.062 (0.059)	0.015 (0.056)	0.047^{+} (0.028)	0.046^{+} (0.027)	−0.031 (0.051)
Top 5 × Material	0.254* (0.123)	0.117 (0.105)	0.138^{+} (0.078)	−0.003 (0.043)	0.120 (0.098)
Top 5 × Aerospace	0.010 (0.061)	0.004 (0.058)	0.006 (0.033)	0.096* (0.046)	−0.092* (0.044)
Top 5 × Physics	−0.072 (0.259)	0.068 (0.256)	−0.140 (0.217)	−0.162 (0.241)	0.230* (0.108)
Top 5 × Other	0.071 (0.099)	0.069 (0.092)	0.001 (0.054)	0.075** (0.023)	−0.005 (0.088)
Female	0.030 (0.028)	0.038 (0.026)	−0.008 (0.016)	0.030^{+} (0.018)	0.008 (0.022)
Major Main Effects					
Computer Science	0.116 (0.102)	−0.004 (0.092)	0.120* (0.060)	0.016 (0.018)	−0.020 (0.089)
Electrical Eng.	0.004 (0.100)	0.013 (0.092)	−0.009 (0.055)	0.041^{+} (0.022)	−0.028 (0.088)
Mechanical Eng.	−0.002 (0.105)	0.003 (0.097)	−0.005 (0.056)	0.046 (0.028)	−0.043 (0.092)
Chemical Eng.	0.002 (0.112)	−0.012 (0.102)	0.014 (0.066)	0.022 (0.032)	−0.034 (0.097)
Civil Eng.	−0.057 (0.107)	−0.020 (0.098)	−0.037 (0.056)	0.011 (0.023)	−0.031 (0.095)
Material Science	−0.264* (0.111)	−0.149 (0.092)	−0.115 (0.072)	−0.008 (0.030)	−0.141 (0.088)
Physics	0.211 (0.250)	0.067 (0.247)	0.144 (0.215)	0.246 (0.236)	−0.179* (0.091)
Obs.	2470	2470	2470	2470	2470
Mean of DV (Not Attending Top 5 IIT)	0.305	0.211	0.094	0.042	0.167
R2	0.097	0.094	0.112	0.106	0.085

Notes: This Table investigates whether attending a Top 5 IIT is more or less strongly associated with migration, depending on the major of study. The main effect of aerospace drops out due to there being (in our sample) no one studying aerospace outside the Top 5 IITs. Robust Standard errors in parentheses. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Appendix Table A7
Controlling for Course Selectivity

	Migrated	Migrated Grad	Migrated Work	Migrated PhD	Migrated Master
	(1)	(2)	(3)	(4)	(5)
Attended Top 5 IIT	0.043^{+} (0.024)	0.050* (0.022)	−0.007 (0.015)	0.055** (0.013)	−0.004 (0.020)
Course Selectivity	−0.002 (0.002)	−0.003^{+} (0.001)	0.001 (0.001)	−0.003** (0.001)	0.001 (0.001)
Female	0.033 (0.028)	0.040 (0.026)	−0.007 (0.016)	0.032^{+} (0.018)	0.007 (0.022)
Obs.	2470	2470	2470	2470	2470
Mean of DV (Not Attending Top 5 IIT)	0.305	0.211	0.094	0.042	0.167
R2	0.086	0.089	0.093	0.101	0.081

Notes: Course selectivity is the minimum score required to enter a particular IIT/major combination. Robust standard errors in parentheses. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Table A8
Difference-in-Differences Results

	Migrated	Migrated for graduate school
	(1)	(2)
Attended BHU	−0.046 (0.049)	−0.005 (0.046)
Attended BHU x IIT designation	0.224** (0.063)	0.155** (0.058)
Cohorts Fixed Effects	Yes	Yes
Obs.	1603	1603
Mean of D.V. (from 2009 to 2012)	0.132	0.110
R2	0.037	0.027

Notes: This Table analyzes migration propensities among graduates from three well-respected Indian engineering colleges: a) The Institute of Technology at BHU b) Motilal Nehru National Institute of Technology and c) National Institute of Technology Karnataka. In June 2012, The Institute of Technology at BHU became Indian Institute of Technology (BHU) Varanasi, without concomitant changes to its staffing or curriculum. The other two institutes did not gain IIT designation in this period and are used as controls. The sample goes from 2009 to 2015 (as opposed to 2005 to 2015 in Table 6 due to limited data availability for the two control institutes). Our variable of interest is a dummy taking value one for BHU graduates graduating after 2013, and we control for cohort fixed effects and the main effect attending BHU. Robust standard errors in parentheses. + $p < 0.10$, *$p < 0.05$, **$p < 0.01$.

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