Where Does Top Talent Go to College? Global Talent Allocation and Its Consequences

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Abstract

The world's highest-potential students may be unable to attend leading universities, which concentrate in a handful of countries. Such "undermatch" can be a problem if student potential and university quality are complements in the creation of social value. To study the allocation of top global talent to universities and its consequences, we assemble undergraduate and career histories for 11,424 International Mathematical Olympiad participants. We present three main findings. First, we estimate that 31% (48%) of recent medalists attend a top-10 (top-50) university, with substantial geographical heterogeneity: the main predictor of whether a medalist attends a top university is whether their origin country has one. Second, the undermatch appears consequential. Conditional on individual characteristics including initial math ability, attending a better-ranked university predicts a higher probability of earning top-10 PhD degrees, winning major scientific prizes, and working in a top tech firm. Sensitivity analysis suggests that an unobserved factor would have to matter substantially more than initial math ability to explain these associations away. Third, we present an evidence-based discussion of the reasons behind the undermatch and of which policies could be most effective in ensuring that the world's best students have a shot at attending the best universities.

Keywords: talent allocation, university quality, high-skill migration, developing countries

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1 Introduction

Individuals with high potential to develop new science and technology can be widely distributed across geographies, cultures, and social strata, but they may be unable to reach their potential due to frictions, bottlenecks, or other reasons. Globally, university training may be an especially important bottleneck, since the best universities are highly selective and located in just a handful of countries, which can lead to top talent being "undermatched," i.e., the students with the highest potential may fail to attend the best universities. Migration barriers may not only lead to worse economic outcomes for potential migrants (Gibson and McKenzie, 2012; Barsbai et al., 2026) and lower domestic human capital development (Batista et al., 2025, 2012; Abarcar and Theoharides, 2024), but can also represent substantial global costs, as the capacity for innovation of these high-potential individuals can remain underdeveloped (Hsieh et al., 2019; Romer, 2000). Hence, it is important to understand the size of this misallocation in the training of university-level talent, whether it is really consequential for the advance of science and innovation, and the reasons behind it.

To explore those questions, we study the trajectories of participants of the International Math Olympiad (IMO). We use it for two main reasons. First, the IMO is an annual competition in which over 100 countries each send up to six of their best pre-university students, and, because of that, it naturally delivers a sample of the world's top math talent. Second, since every participant sits the same two-day exam, IMO scores are a globally comparable ability signal that can distinguish math ability even among students who would ace the math SAT (Ellison and Swanson, 2010). The existence of this signal not only allows us to account for initial ability in our analysis, but also suggests that the undermatch among IMO participants may be a lower bound on the global figure, since other students may lack such a strong and precise signal of ability.

For this paper, we build a novel dataset documenting the undergraduate and career histories of 11,424 IMO participants from 132 countries between 1981 and 2020. To do so, we combine

manual coding, LLM-assisted web search, and online professional profiles (LinkedIn-based) from Revelio Labs. We find undergraduate institutions for 80 percent of medalists and 55 percent of all participants. For the recent years, our coverage of medalists reaches 85%, and validation against Cambridge and MIT administrative records confirms that we are able to find nearly all participants who attended "top" institutions.

We begin our analysis by asking how well the world's best math talent is allocated across universities. For this, we focus on IMO medalists, roughly the top half of participants, who we know win scientific prizes at rates far exceeding those of top-university undergraduates (Agarwal et al., 2025). Among 2015–2020 medalists, at least 29% attended a top-10 university and at least 75% a top-500 institution, where rank is the better of a university's QS World and QS Mathematics 2020 rankings. To estimate the total shares, we simulate the allocation of the 14% of medalists whose university we could not find. We assume that the probability that a "not found" medalist actually attended a given top-10 university is proportional to the number of medalists we found there times the share of medalists we missed at Cambridge and MIT, and that the share of medalists we missed becomes monotonically larger for lower-ranked universities. Our simulations indicate that 30.5–32.1% of medalists attend a top-10 university, 53.3–55.4% a top-100, and 83.3–85.5% a top-500. Hence, we see substantial undermatch: nearly half of the world's best young mathematicians attend universities outside the top 100 institutions.

We then study the predictors of the undermatch. We regress top-university attendance on individual characteristics—cohort, IMO score and participation frequency, and gender—and country of origin characteristics. Gender and IMO performance strongly predict top university attendance, but where a medalist is born matters more than how well they score: medalists whose country hosts a top-10 university are 60pp more likely to attend one—three times the placement difference associated with the full range of IMO performance. A bronze medalist from the US or UK is more likely to reach a top-50 institution than a gold medalist from a country without one; 27% of developing-country medalists attend a top-10 university, against

near-universal placement from the US and UK. These patterns could be explained by preferences for staying home, costs, frictions, or university admission policies. As this undermatch could be inconsequential (e.g., because the best students find their way to the best PhD programs regardless of where they receive their undergraduate training), we turn our attention to the association between top university attendance and career outcomes before discussing the reasons for the undermatch.

To explore the association between top university attendance and socially desirable outcomes, we focus on four proxy outcomes: a top-10 PhD (frontier research training), a major academic prize (scientific contribution), employment at a leading technology firm (innovation), and founding or leading a company (entrepreneurship). Our analysis compares similar IMO competitors (e.g., in terms of math ability, country of origin, age) who attended higher- or lower-ranked institutions using multivariate regressions, so we are careful about assigning causality to the associations. Estimating such associations in the sample of competitors from 1981 to 2005, we find that attending higher-ranked universities is strongly associated with better academic outcomes. Relative to attending universities outside the top 500, top-10 attendance is associated with increases of 34pp in top-10 PhD attainment and 17pp in major prizes, both significant at the 1% level; attending top-10 universities is also associated with higher chances of employment in a leading tech firm (10pp, $p < 0.001$) and of becoming a founder or CEO (5pp, $p = 0.08$). These associations are large relative to sample averages of 9%, 12%, 4%, and 7%, and sensitivity analysis (Cinelli and Hazlett, 2020) indicates that a confounder would need to be at least 28 times as strong as IMO score to explain away the associations with academic outcomes, and 26 times as strong for non-academic outcomes. Against the more demanding benchmark of all country-of-origin fixed effects, the academic associations shrink but remain large, while the non-academic ones vanish.

Two other patterns provide extra evidence for the thesis that matching top STEM talent with specific top universities generates positive social returns. First, the top-university premia in scientific outcomes generally rise both with university rank and IMO performance. For in-

stance, relative to attending universities outside the top 500, the top-10 premium in top-10 PhD attainment rises from 26pp in the lowest performance quartile to 43pp in the highest, and the premium in major prizes from 14pp to 28pp. Among competitors in the top quartile of performance, returns are higher for top-10 than for top-11-to-500. For industry outcomes, there is no clear evidence of assortative matching returns throughout the IMO ability range. Second, when estimating university-specific returns, we see that different institutions appear to offer different advantages, increasing the potential for matching gains. For instance, with the same controls as in previous specifications, Stanford attendance is much more predictive of industry outcomes, while Princeton attendance is much more predictive of academic outcomes. Because each tier premium averages over universities that are strong in different outcomes, the tier-based estimates likely understate the returns to matching students with the right universities.

Lastly, we discuss the possible reasons behind the undermatch, and the associated policy implications. We first consider taste for staying home. Survey evidence shows that 81% of IMO participants from developing countries aspire to study in the US or UK and only 11% in their home country (Agarwal et al., 2021), yet only 17% of developing-country participants in our data attend a US or UK university. Differences in taste for staying home are also unlikely to explain why IMO score and gender predict placement in the way they do, as that would require lower-scoring and male students to prefer to stay home more often. More likely, those associations reflect universities' admission policies. Next, we consider whether information about ability is used effectively in the matching process. We find evidence that it is not: in a regression discontinuity design, students who barely earned a gold medal were 10.9pp ($p = 0.03$) more likely to attend a top-10 university than those who barely missed it. The bronze and silver cutoffs show no such jumps. Finally, we consider the role of student financing, aid, and information. A four-year top-10 degree costs about $360k at sticker price, yet several top US universities meet the full financial need of the international students they admit, so the obstacle may be less the price than the availability of such seats, or the fact that such funding is uncertain (e.g., as in Dynarski et al. 2021).

Taken together, our results indicate that a large share of the world's top STEM talent does not attend the universities that can best prepare them to contribute to science and innovation, as that is true even among those who carry one of the most legible ability signals available—IMO medalists. Because the outcomes we study proxy for the social returns of science and technology development, this undermatch can carry meaningful social costs. The evidence points to admission and application frictions, more than to a taste for home, as the main sources of the undermatch, but our data cannot pin down their relative importance, as we do not observe where medalists apply, nor what they believe about their chances of admission and the costs of applying. In an exploratory exercise, we estimate a model in which students decide whether and where to apply and universities decide whom to admit—with its identification resting on strong functional form assumptions. The estimation results suggest that guaranteeing admission at the top-10 universities would reduce the undermatch more than removing the perceived one-time costs of entering the US and UK application systems, which in turn would do more than covering tuition and living costs.

We make three main contributions. First, we extend the study of talent misallocation to the global allocation of students across universities. Hsieh et al. (2019) show that barriers facing women and Black men misallocated talent across US occupations; in our data, the analogous binding constraint is country of origin. Moser et al. (2014) show that moving top scientists across countries can raise innovation in their new environment; we study an earlier margin, whether the most able students reach the universities that can best train them. A literature on access to opportunity shows that family background and childhood environment shape who innovates (Novosad et al., 2024; Bell et al., 2019; Chetty et al., 2026), and, in the United States, that most high-achieving, low-income students never apply to selective colleges despite generous aid (Hoxby and Avery, 2013; Hoxby and Turner, 2015); we document similar barriers across countries, at undergraduate education, where country of origin plays the role that family income and neighborhood play within countries, and where admission and application frictions appear to matter more than prices.

Second, we contribute to the literature on the returns to attending selective colleges and on assortative matching. Average earnings returns range from near zero to large, and, reviewing this literature, Bleemer and Rothstein (2026) conclude that they do not rise with prior achievement.[1] Most of these studies, however, concern students below the very top of the ability distribution. A notable exception is Chetty et al. (2026), which estimates the effects of attending an Ivy-Plus college: it cannot reject that the returns are constant across SAT/ACT score bands. Nevertheless, its test has low power, and its point estimate of the effect on the predicted probability of reaching the top 1% of earnings is the largest for the highest scorers. Here, we focus on whether attending a higher-ranked university matters at the extreme right tail of ability and for outcomes that proxy for contributions to science and innovation—an understudied margin (Bleemer and Rothstein, 2026). Closest to our approach, Dillon and Smith (2020) also rely on selection on observables and find complementarity between student ability and college quality in on-time graduation and long-run earnings among US four-year college entrants; among IMO participants, we find a similar pattern for academic, though not industry, outcomes. Finally, because our sample includes participants of similar ability who never applied to top universities, we measure undermatch that arises before admission, which designs comparing students admitted to the same colleges cannot capture.

Third, we complement the literature on brain drain (for reviews, see Docquier and Rapoport, 2012; Gibson and McKenzie, 2011a) and provide the most comprehensive tracking of where the world's top math talent goes to college. High-skilled migration affects both migrants and their origin countries, and a growing literature studies its effects on migrants' earnings (e.g., Gibson and McKenzie, 2012), remittances (e.g., Gibson and McKenzie, 2012), scientific production

[1]These studies use admission cutoffs, affirmative-action reforms, or comparisons of students admitted to the same set of colleges. Returns are near zero in Dale and Krueger (2014) and Mountjoy and Hickman (2021) and large in Hoekstra (2009) and Anelli (2020); they are larger for disadvantaged students in Dale and Krueger (2014) but not in Zimmerman (2019). If anything, returns fall with prior achievement (Bleemer, 2022; Barahona et al., 2026), and lower-testing students benefit as much as (Mountjoy and Hickman, 2021) or more than (Bleemer, 2024) higher-testing ones. In California, students admitted through affirmative action or a top-percent policy, with test scores well below those of typical admits, gain more than the estimated value-added of their institutions (Bleemer, 2022, 2024).

(e.g., Gibson and McKenzie, 2014; Kahn and MacGarvie, 2016; Agarwal et al., 2023), and human capital acquired at home in anticipation of migrating (e.g., Beine et al., 2008; Batista et al., 2012; Chand and Clemens, 2023; Abarcar and Theoharides, 2024; Khanna and Morales, 2025). Here, like Barsbai et al. (2026), we focus on international educational migration, i.e., moving abroad for a university education. We differ in our focus on top math talent, identified by the IMO, which allows us to study how those educational migration decisions are associated with long-term career outcomes, such as scientific discoveries, that may carry global positive externalities. Prior studies of top students are narrower: Gibson and McKenzie (2011b, 2012) track top secondary-school graduates from up to five countries, including members of New Zealand's Mathematical Olympiad team, to study their emigration and return decisions and the consequences of their emigration, recording the country but not the institution where they earned their degrees; Agarwal and Gaule (2020) find that IMO participants from developing countries produce fewer publications but do not track undergraduate institutions; Yuret (2024) tracks 2,785 medalists' careers but does not link outcomes to the university attended; Choudhury et al. (2023) study top IIT-JEE scorers in a single country. We cover 11,424 participants from 132 countries over four decades, validate the attendance data against administrative records, and also collect data on several career outcomes.

2 Conceptual Framework

In this section, we provide an organizing framework of university choice. The stylized model serves two *illustrative* purposes. First, it lays out the trade-offs faced by a high-ability student choosing where to study. Second, it shows why even unconstrained privately optimal choices can be socially suboptimal: part of the return to developing exceptional talent—discoveries, technologies, new firms—accrues to society at large as a positive externality, so top talent may underinvest in training quality.

Assume that students, indexed by i, with ability a_i, home country $c(i)$, and wealth w_i decide

which universities to apply to and, later, which to attend. Universities have quality q_u and a student-specific net-of-aid price p_{iu}. Attending university u yields a payoff

$$U_{iu} \;=\; \underbrace{v(q_u, a_i)}_{\text{career value}} \;+\; \underbrace{h_i \mathbb{1}_{c(u)=c(i)}}_{\text{home taste}} \;-\; \underbrace{\eta_i\, p_{iu}}_{\text{price}} \tag{1}$$

The home term $h_i \geq 0$ is genuine attachment—family, language, the wish to stay—distinct from the frictions of leaving. The marginal utility of money η_i may vary with family wealth and with the credit environment at home.

Application decisions. Applying to foreign universities is costly. Let each application carry a (perceived) cost $\kappa_{iu} \geq 0$: application and testing fees, translating credentials, the information to navigate a foreign system, visa uncertainty. A student applies to u when its option value—the admission probability π_{iu} times the expected utility gain should u prove her best admit—exceeds κ_{iu}. We also let admission probabilities $\pi_u(X_i)$ depend on student characteristics X_i, such as ability, gender, and country of origin.

Hence, the probability that a student attends a certain institution depends on all the preceding factors:

$$\Pr\big(\text{student } i \text{ attends } u\big) \;=\; f\Big(\underbrace{v(q_u, a_i)}_{\substack{\text{private}\\ \text{value}}}, \underbrace{h_i \mathbb{1}_{c(u)=c(i)}}_{\text{home taste}}, \underbrace{p_{iu}}_{\text{price}}, \underbrace{\kappa_{iu}}_{\substack{\text{application}\\ \text{costs}}}, \underbrace{\pi_u(X_i)}_{\substack{\text{admission}\\ \text{probability}}}\Big), \tag{2}$$

increasing in private value and admission probability, decreasing in prices and application costs, and shifted toward home institutions by home taste. In Section 4, we estimate how the observable factors in equation (2) predict the probability that students attend the best universities. In Appendix E, we fully specify and estimate a model, to disentangle the taste parameters from the cost barriers under restrictive assumptions.

Private versus Social Optimum. Suppose that the match between talent and training also produces a positive externality—value the student does not capture, $s(q,a_i)$— so that the total value of the university is $v(q,a_i)+s(q,a_i)$. This social value may include knowledge spillovers from research, surplus from technologies and firms not appropriated by their creators, and the training of others. We hypothesize that $s_q \geq 0$ and $s_{qa} \geq 0$: external returns rise with training quality, and more steeply for more talented students. This is the standard justification for subsidizing science (Romer, 2000). Since students do not internalize the social value s_q, they may underinvest in university quality q, as long as attendance costs increase with quality. In Section 5, we probe the extent to which this social value is meaningful, and whether $s_{qa} \geq 0$, by estimating how top-university attendance predicts joining a top-10 PhD program, receiving prestigious prizes, working in tech, or creating firms while conditioning on students' initial characteristics.

Besides the fact that bright students do not fully internalize the social value of their training, there are at least two other sources of inefficiency in university choice. First, credit constraints distort the choice among admissions: a constrained student over-weights price relative to career value v and chooses lower quality than she would with perfect credit. Second, students decide where to apply under imperfect information: a student who overestimates application costs or underestimates her chances of admission may never apply to universities that would admit and fund her. Even within the US, most high-achieving, low-income students apply to no selective college despite facing net prices below those of the colleges they attend (Hoxby and Avery, 2013). Informing them of net costs and the application process raises applications (Hoxby and Turner, 2013), as does guaranteeing free tuition upfront while leaving the expected price essentially unchanged (Dynarski et al., 2021). Foreign applicants may have even worse information.

3 Context and Data

3.1 Context

The International Mathematical Olympiad (IMO) is an annual competition for pre-university students, held since 1959. Contestants sit a two-day exam of six problems; because problem difficulty varies, we normalize total scores to within-year percentiles. Participation expanded from roughly 30 countries in the early 1980s to over 100 by 2020. Each national team is selected through multi-round procedures that filter students down to six competitors, selecting the extreme right tail of the within-country math ability distribution. Agarwal et al. (2025) shows that even bronze medalists go on to win major scientific prizes at rates exceeding those of undergraduates at any top-10 university, confirming that IMO selection identifies genuinely exceptional talent rather than mere test-taking skill. We focus on 1981–2020, which yields 11,424 unique participants from 132 countries.

3.2 Data

We build our data in three steps: (i) manual biography coding of medalists, (ii) automated LLM-based data collection for all participants, and (iii) LinkedIn profile matching. Our cleaned data covers 11,424 participants, of whom 5,784 are medalists (1,128 gold, 1,966 silver, 2,690 bronze).

3.2.1 Manual Biographical Data Collection

We began with a multi-step manual procedure covering the 5,784 medalists only. A team of freelancers searched for each medalist's bachelor's-degree institution using LinkedIn, personal and faculty webpages, competition records (Putnam, IMC), and social media, recording a profile URL for verification. Research assistants quality-checked the coding and harmonized institution names. In this search, we found an undergraduate institution for 70% of the 1980–2020

medalists.

3.2.2 Automated Data Collection

To extend coverage beyond medalists and to collect career outcomes, we deployed OpenAI's GPT-5 via the API, with web search enabled. For each of the 11,424 participants, the model received the participant's name, country, and last year of IMO participation, then searched the web, including personal websites, institutional pages, and local-language media sources, cross-checking any candidate profile against the IMO participation timeline. The exact prompt is reproduced in Appendix F.

The model returned structured data on each participant: whether a profile was found, a brief biography, broad field of work, undergraduate and doctoral institutions, and a list of major international prizes or honors.[2] A second LLM call, without web search, classified each biography and field of work into binary indicators for academia, mathematics, finance, IT, and founding or leading a company (Appendix F). Local-language search—Mandarin, Russian, Arabic, Vietnamese—matters because many participants' online presence is not in English.

The LLM found at least some biographical information for 82% of participants and identified an undergraduate institution for 52% of medalists and 34% of non-medalists. Where both sources identified a bachelor's institution, the LLM matched the manual coding 90% of the time; an audit of 50 random discrepancies showed that most arose from attendance at multiple institutions (a transfer or an integrated degree coded differently). Preserving manually verified data wherever available, we use LLM institutions only where manual coding found none, raising medalist coverage from 70% to 78%.

[2]Among all participants, 1,154 had at least one career-level recognition reported by the LLM. We supplemented this procedure with data from Agarwal et al. (2025), which matched olympiad medalists to major international scientific prizes and fellowships; the LLM-based procedure had missed prizes for only 12 IMO medalists, and we amend our data accordingly.

Universities and rankings. Raw institution names from both the LLM and manual coding were matched to OpenAlex (Priem et al., 2022), which provides unique identifiers and country codes and resolves parent–child ambiguities (e.g., mapping École Polytechnique to Institut Polytechnique de Paris). We linked each institution to the 2020 QS World and QS Mathematics rankings and assigned it the better of the two ranks—henceforth "university rank" (Appendix Table A.1 lists the top-10 and top-50 institutions under this ranking). Among the major alternatives, this combination covers most of the institutions participants attend and least contradicts the revealed preferences of medalists who stay in their home country—students who face no migration barrier.[3] Our main results are similar if we use instead the Shanghai ranking.

3.2.3 Complementary Data Sources

LinkedIn data. We first searched for candidate LinkedIn profile matches (via Revelio Labs) by fuzzy name matching.[4] A probability forest then selected the best candidate for each participant—or classified them as having no LinkedIn presence—using 43 predictors covering name characteristics, IMO performance, education timing and field alignment, career sector, and cross-source agreement. The forest was trained on medalists with a LinkedIn URL verified by research assistants. We retained the top 70% of match scores, identifying a profile with high confidence for 37% of participants (4,213), and extracted education histories, career positions, and company information. All main results are robust to using 100% or only 25% of the sug-

[3]We compared twelve global rankings, all at their 2020 editions—QS World and QS Mathematics, Shanghai (ARWU) general and mathematics, THE, CWUR, NTU, URAP, SCImago, Leiden, Nature Index, and Webometrics—as well as the combinations of the general and mathematics editions of QS and of Shanghai, on two criteria. The first is coverage of the institutions medalists attend. The second is agreement with the choices of medalists who study in their home country. Within each country, for every pair of institutions such medalists attend, we check whether the ranking places the more popular institution higher, weighting each pair by the squared difference in enrollment and counting ties and unranked pairs as half a disagreement. The combined QS ranking covers 76% of attended institutions and misorders 15.2% of weighted pairs, the lowest share of any ranking or combination.

[4]We split each name into words and encode each word by its pronunciation (Metaphone 3), so that spelling variants of the same word share a code. Any LinkedIn profile containing a word with the same code as a word in the participant's name becomes a candidate. We score each such word pair by one minus its Damerau–Levenshtein distance—the number of insertions, deletions, substitutions, and transpositions of adjacent characters needed to turn one word into the other—relative to word length, and sum the word scores into a profile score that ranks the candidates.

gested matches and to dropping the 10% of participants with the most frequent names (Appendix Tables A.10 and A.11). Where sources conflict, manual coding takes precedence over the LLM, and the LLM over LinkedIn; LinkedIn fills the remaining cases, raising the share with an identified undergraduate institution to 80% for medalists and 55% for all participants.

Participant disambiguation. Because participants can compete in multiple years, we consolidate entries belonging to the same individual. We flag a pair of participations as a potential match when the names are close in string distance and the countries are the same or closely tied (e.g., the former Soviet Union or Yugoslavia, or the U.S. and Puerto Rico). If names and countries match exactly and the participations are one or two years apart, we accept the match; otherwise we resolve each pair by manual inspection and internet searches.[5] When biographical searches revealed that a competitor was listed under a different name or name ordering across years, we also merged those identities.

3.2.4 Validation of University Coding

We validated our combined university coding against two external administrative sources (see Appendix D for a complete description). First, MIT's Registrar verified the full list of 2015–2020 medalists against enrollment records. Among 2015–2020 medalists, our combined coding (manual + LLM + LinkedIn) identifies 114 MIT undergraduates, and the Registrar's records reveal 8 more. Second, we matched medalists against Cambridge University graduation yearbooks (2018–2023), where names appear as first initial plus surname. Our combined coding identifies 85 Cambridge medalists among 2015–2019 medalists; yearbook matching suggests approximately 14 additional medalists not captured (adjusted for the expected false-match rate). We interpret these results as evidence that our data collection procedure captures about nine in

[5] Within each country or group of tied countries, we flag pairs whose standardized names are identical, pairs in which one name contains the other, and pairs whose names share the first two characters of their Double Metaphone code—a phonetic encoding under which spelling variants share a code—and lie within a Jaro-Winkler distance of 0.10. The Jaro-Winkler distance runs from 0 (identical names) to 1, counts matching and transposed characters, and gives extra weight to agreement at the start of the names. Within our 1980–2020 window, we found no distinct individuals sharing the same name and country.

ten of the medalists who attended the world's most desirable institutions.

The miss rate falls by about half a percentage point per cohort year (27% for 1981–2000 vs. 14% for 2015–2020), is lower for stronger performers, and is higher for low- and lower-middle-income origins (Appendix Table A.2).

4 Where Does the World's Top Math Talent Go to College?

4.1 The Global Allocation of Medalists

In this section, we describe the allocation of top math talent across universities, focusing on the IMO medalists of 2015–2020.[6] Table 1 describes these 1,132 medalists. Using our combined ranking (the better of the QS World and QS Mathematics rankings; see Section 3), at least 29% attend a top-10 university and at least 75% a top-500 institution; 21% attend MIT or Cambridge, the top destinations for medalists. Just over half (52%) come from developing countries and 6% are female. We could not find an undergraduate institution for 14% of medalists in this cohort, so the observed attendance shares are lower bounds.

To estimate the true shares above each rank, we simulate where the 14% of medalists whose university we could not find studied. The simulation rests on two assumptions. First, as the validation implies that we should have inflated the MIT and Cambridge observed counts by 1.11 to get to the true attendance numbers (Appendix D), we expect the same inflation factor to apply to other top-10 universities. Second, that inflation factor increases linearly with rank, at the rate that allocates all medalists.[7] The gap between the inflated and the observed count at each rank is the expected number of medalists we missed there. Each medalist whose university we could not find then draws a rank with probability proportional to that gap, and we repeat the draws

[6] Results for the 1981–2000 and 2001–2014 cohorts appear in Appendix Table A.3 (descriptive statistics) and Appendix Tables A.4 and A.5 (predictors of attendance).

[7] Let n_r be the observed number of medalists at rank r. For $r \leq 10$, $\hat{n}_r = n_r$ at MIT, whose count includes the Registrar's records, $n_r + 16$ at Cambridge, which adds the medalists the yearbooks suggest we still miss there, and $1.11\,n_r$ elsewhere; for $r > 10$, $\hat{n}_r = n_r(1.11 + 0.11\,\alpha\,(r-10))$, with $\alpha = 0.003$ calibrated so the total equals the number of medalists. Medalists at institutions without a QS rank enter at $r = 1{,}501$, just below the lowest rank.

1,000 times. Across simulations, 30.5–32.1% of medalists attend a top-10 university, 53.3–55.4% a top-100, and 83.3–85.5% a top-500 (Figure 1 plots the median cumulative allocation with 95% bands, which reflect the randomness of the draws). The second assumption matters little. Because the inflation factor is pinned at the top and because all medalists need to be allocated, other (nonlinear) monotonically increasing forms give very similar results.

4.2 The Gap by Access and Development Status

Figure 2 disaggregates the allocation estimates by access to top universities: medalists from the US and UK, from countries hosting a top-10 university in our combined ranking (the US, UK, and Switzerland), from countries hosting a top-50 but no top-10 university, and from advanced and developing economies.[8] Medalists with a top-10 university at home almost all attend one: 95% of US and UK medalists attend one, or 89% adding Switzerland. Those numbers should be close to the social optimum if the social returns to university attendance rise with university quality and more steeply for the most talented (see Section 2). The remaining groups fall far short: top-10 attendance is 27% among medalists whose country hosts a top-11–50 university, 36% across advanced economies as a whole, and 27% in developing countries. Medalists with a top-11–50 university at home thus reach the top 10 no more often than developing-country medalists, even though 66% of them attend a top-50 university, largely through those domestic options.

4.3 Predictors of Placement

We begin by describing how observable factors predict placement at top universities with reduced-form linear probability models such as:

$$\mathbb{1}_{\text{Rank}_i \leq k} = \alpha + \beta\, Perf_i + \phi\, Female_i + \lambda\, HasTopK_{c(i)} + \gamma_{y(c(i))} + \eta_{t(i)} + \varepsilon_i \tag{3}$$

[8] Developing countries are non-high-income economies per the World Bank classification.

where i indexes individuals, $c(i)$ maps them to their country of origin, and $y(c)$ maps countries to income levels. $\mathbb{1}$ is the indicator function, $Perf_i$ is the participant's best IMO score percentile, $Female_i$ is a gender indicator, $HasTopK_{c(i)}$ indicates that $c(i)$ hosts a top-k university (overall or mathematics), $\gamma_{y(c(i))}$ are income-level (World Bank group) fixed effects, and $\eta_{t(i)}$ are last-competition-year fixed effects. Medalists whose institution we could not find are coded as not attending a top institution, but results are similar if they are dropped (Appendix Table A.6). These conditional correlations are descriptive; they represent a "reduced form" generated by the decision problem of Section 2. Three patterns emerge (Table 2).

First, two patterns suggest that universities' admission preferences may play a big role. One is that higher-scoring medalists attend better universities, as each percentile of IMO performance is associated with a 0.3–0.4pp increase in the probability of attending a top-10 or top-50 ($p < 0.05$). Preferences could in principle drive these positive associations, but only if lower-scoring medalists placed substantially lower private value on attending a top university. More likely, universities select students on math ability, even in the ability range above the top of the SAT (Calaway, 2026). Among the 215 medalists without a domestic top-500 university, who typically score lower and face more migration frictions, score does not predict top-500 attendance. The other is that female medalists are 20–25pp more likely to attend a top-10 university than male medalists with the same scores and origin (19–24pp for top-50 and 12–13pp for top-500, all $p < 0.05$; 19pp in the small conditional top-500 sample, $p = 0.21$). As there is no clear reason to expect that girls are much more eager to migrate than boys of similar backgrounds, this also suggests that universities' admission criteria play an important role.

Second, placement tracks geography. Country fixed effects explain substantial variation (see R^2 in columns 1, 4, 7), and country covariates (columns 2, 5, and 8) suggest one reason why: hosting a top-k university is associated with 60pp higher top-10 attendance, 32pp for top-50, and 22pp for top-500 (all $p < 0.001$). By comparison, the full 50-percentile range of medalist IMO performance shifts top-10 placement by 16–20pp and top-50 placement by 14–19pp: country of origin predicts placement more strongly than performance does. In Section 6, we discuss

whether this home bias reflects a taste for staying home or other factors.

Third, national income predicts placement in some specifications, but neither consistently nor always with the expected sign. Conditional on domestic availability of a top-k university, income predicts relatively little variation: among medalists whose country hosts none (columns 3, 6, 9), low- and lower-middle-income medalists are 8pp less likely than high-income peers to reach a top-10 university ($p = 0.02$), but that correlation flips when predicting top-50 attendance (+9pp, $p = 0.04$). One reading is that medalists' family income differences *within* these groups are small relative to the full cost of applying to and attending a top university abroad, so they rarely tip the decision. Another possibility is that home taste increases with origin income, generating countervailing effects.[9]

Medals versus borders. Figure 3 illustrates the point medal by medal. Among medalists from countries with a top-50 university (excluding the US and UK) whose undergraduate institutions we could find, 66% of bronze, 75% of silver, and 82% of gold medalists attend a top-50 institution; from countries without one, the shares are 37%, 43%, and 60%. A bronze medalist from the US or UK is more likely to attend a top-50 university than a gold medalist from a country without one—every US and UK bronze and silver medalist in our data attends a top-50 institution. These figures condition on a found institution and are likely optimistic: medalists whose institution we could not find likely attended lower-ranked institutions, so the true shares are lower in both groups.

5 Undermatch and Career Outcomes

Section 4 documented that a large share of the world's top math talent does not reach the best universities, and that domestic access to top universities is the strongest predictor of who does.

[9] Slovakia is the extreme case: high income and no top-500 university at home, yet half of its sixteen 2015–2020 medalists stay at the domestic flagship (ranked outside the top 500) and four of the rest enroll in Prague, Brno, or Budapest; only three reach a top-10 university.

This section examines whether attending a higher-ranked university is associated with career outcomes that proxy for the social value of top talent—the term $s(q, a_i)$ in the framework of Section 2—or whether top talent achieves similar outcomes at any university. Although we lack exogenous variation in university attendance, we show here that attending higher-ranked universities is predictive of career choice and success even after controlling for initial ability, country of origin, and other factors.[10] Sensitivity analyses also suggest that omitted factors are unlikely to explain away these associations. We focus on the four outcomes that proxy for social value: completing a top-10 PhD, winning a major academic prize (e.g., an international scientific prize or fellowship; see Section 3), working in a leading technology firm, and becoming a founder or CEO.

For this analysis, we expand the sample from medalists to all IMO participants, which increases our power. We follow participants whose last competition was in 2005 or earlier, allowing at least 20 years for careers to develop, and restrict to participants from outside the US and UK ($N = 5{,}928$), since nearly all US/UK participants attend top universities. We estimate:

$$Y_i = \sum_k \beta_k \mathbb{1}_{\text{Tier}_i=k} + \mathbf{X}_i'\gamma + \delta_{c(i)} + \eta_{t(i)} + \varepsilon_i \tag{4}$$

where Y_i is a career outcome for participant i, $\mathbb{1}_{\text{Tier}_i=k}$ are indicators for the university tier of i's undergraduate institution, $\mathbf{X}_i$ is a vector of individual controls (a quadratic in the participant's best IMO score percentile, a gender indicator, and fixed effects for the number of IMO participations), $\delta_{c(i)}$ are country-of-origin fixed effects, and $\eta_{t(i)}$ are last-competition-year fixed effects. Participants whose undergraduate institution we could not find (54% of the sample) are included in an additional university tier, "UG not found," but results are similar, if somewhat smaller, when we drop them (Appendix Table A.7).

[10] Natural experiments, such as the dissolution of the Soviet Union or shifts in US immigration restrictions, could help identify the effects of increased access to top universities. In exploratory analyses, we tested whether several such natural experiments produced a "first stage" on top-university attendance, but all estimates were either weak or unreliable. Similarly, the medal cutoffs examined in Section 6.2 do not generate variation in university placement among the 1981–2005 cohorts (the cohorts in this exercise; see Appendix Figure A.2).

5.1 Career Outcomes and University Rank

Relative to participants outside the top 500, attending a top-10 university is associated with a 34pp increase in the probability of earning a PhD from a top-10 institution ($p < 0.001$; Table 3), a 17pp increase in winning a major academic prize ($p < 0.001$), a 10pp increase in working at a leading technology firm ($p < 0.001$),[11] and a 5pp increase in becoming a founder or CEO ($p = 0.08$). These coefficients are large relative to sample averages of 9% (top-10 PhD), 12% (major prizes), 4% (leading tech firm), and 7% (founder/CEO). The magnitudes are broadly consistent with the quasi-experimental estimates of the effects of attending Ivy-Plus universities on attending elite graduate schools or working for elite employers by Chetty et al. (2026).

The gradient across tiers is monotonic for PhD placement and leading tech firm employment. Attending a university ranked 11–50 is associated with an 8pp increase in top-10 PhD rates ($p < 0.001$)—one-quarter the top-10 coefficient—and attending one ranked 51–500 with a 3pp increase ($p = 0.04$); for leading tech firm employment, the coefficients fall from 10pp (top-10) to 7pp (11–50) and 2pp (51–500; all $p < 0.05$). For prizes, the gradient flattens below the top 10: attendees of universities ranked 11–50 and 51–500 are equally likely to win a major prize, 10pp more than participants outside the top 500 (both $p < 0.001$), against 17pp for the top 10. Restricting to participants with a found institution yields smaller but still significant coefficients—31pp for top-10 PhD, 9pp for leading tech firm (Appendix Table A.7).[12]

University rankings are crude, unidimensional measures of what a university can do. The tiers could mask meaningful heterogeneity, and different universities may confer advantages in different domains, which would be relevant if talented students are heterogeneous in goals and in comparative advantages. To explore this heterogeneity, we replace the tier indicators

[11] Defined as having held a position at any company from the Forbes AI 50 list of top privately held AI companies or a major technology firm (Google, Apple, Amazon, Meta, Microsoft, Netflix, Nvidia, Adobe, Salesforce, AMD, Alibaba, Baidu, Palantir, ByteDance), identified via LinkedIn profiles.

[12] University rank and country are heavily confounded—all but one of the top-10 universities are in the US or UK—so the tier coefficients may partly capture the effects of attending an undergraduate institution in those countries rather than university quality per se. We cannot easily separate the two, because few participants attend a top-10 university outside the US and UK (seven, all at ETH Zurich, four of them Swiss) or a US or UK university ranked outside the top 500 (27).

with indicators for individual universities, keeping the same controls (Appendix Figures A.6–A.8). With few attendees per institution, the estimates are precise enough to be conclusive only for well-populated universities. Among those, no single university drives the estimates. For instance, every top-10 institution with ten or more attendees—MIT, Cambridge, Harvard, Princeton, Stanford, Caltech, and Oxford—shows a positive prize association (4–45pp). Which other outcomes are associated with attendance does vary: Stanford attendance, for instance, correlates more strongly with industry than with academic outcomes (Appendix Figures A.6 and A.7).

5.2 Field Sorting

Top-university attendance is positively associated with having spent time in finance jobs, and negatively associated with being in academia. Using the same specification as equation (4), top-10 attendees are 7pp less likely to have worked in academia than participants outside the top 500 ($p = 0.06$) and 7pp less likely to have worked in math ($p = 0.06$). At the same time, attendees of universities ranked 51–500 are 4pp more likely to have worked in math ($p = 0.06$; Table 3, columns 5–7).[13] Finance shows the reverse pattern: top-10 attendees are 10pp more likely to have worked in finance ($p < 0.001$), while the coefficients for universities ranked 11–50 (4pp) and 51–500 (-0.5pp) are smaller. Hence, the shift into finance is concentrated at the top-10 universities.

The two margins partly arise at different institutions (Appendix Figures A.6–A.8). The exit from academia is concentrated at MIT (-18pp academia, $+11$pp finance) and Stanford (-18pp, $+22$pp); the prize gains are concentrated at institutions whose attendees do not leave academia—Université PSL (École Normale Supérieure) ($+30$pp prizes), the University of Warsaw ($+27$pp), Eötvös Loránd University ($+28$pp), and Moscow State University ($+26$pp prizes, $+19$pp academia). Across universities with ten or more attendees, the prize and academia co-

[13] The field indicators equal one if either the LLM classification (Appendix F) or any LinkedIn position title places the participant in the field at any point in their career.

efficients correlate positively (0.45): universities whose attendees win more prizes also tend to keep them in academia. Part of the top-10 pattern—less academia but more prizes—may therefore reflect averaging over universities that specialize in different careers. That averaging does not explain it entirely, however: MIT attendees, the largest group, are less likely to work in academia ($p < 0.01$) yet more likely to win a major prize ($p < 0.01$).

Because the tier estimates (Table 3) average over this heterogeneity, they may understate the gains from sorting: a student choosing the university strongest on her intended path could realize more than the average tier premium.

5.3 Sensitivity to Selection on Unobservables

Students who attend higher-ranked colleges can be different from those who do not, in dimensions we cannot observe, so the associations above may be due to omitted variable bias. For instance, family wealth or ambition may drive both top-10 attendance and career success. We gauge how strong such a confounder would need to be using the framework of Cinelli and Hazlett (2020), which applies exactly to a single omitted variable and as an upper bound to any combination of them (their Section 4.5). The bias from omitting a confounder depends on only two quantities, both measured net of the controls we include: the share of the remaining variation in top-10 attendance that it explains, and the share of the remaining variation in the outcome that it explains. For any pair of these shares, the Cinelli and Hazlett (2020) framework gives how far the estimate would move toward zero had the confounder been included. We summarize the results by benchmarking the confounder against observed controls. A confounder "k times as strong as IMO performance" explains k times as much of the remaining variation in attendance and in the outcome as IMO performance does.

The conditional associations between career success outcomes and top-10 undergraduate degrees appear robust to confounders several times more relevant than IMO performance. To bring the associations to zero, a confounder would need to be at least 63 (top-10 PhD), 28

(major prizes), 125 (leading tech firm), and 26 (founder/CEO) times as strong as IMO performance (Table 4, Panel A). The estimates change little if the confounder is one, or even three, times as strong as IMO performance: top-10 PhD would fall from 34.2pp to 33.7 and 32.7pp, major prizes from 16.6 to 16.1 and 14.9pp, leading tech firm from 9.9 to 9.8 and 9.7pp, and founder/CEO from 4.9 to 4.8 and 4.4pp (Table 4, Panel A). Without reference to a benchmark, a confounder explaining equal shares of the remaining variation in attendance and in the outcome would need to explain 19.6% (top-10 PhD), 8.5% (major prizes), 8.0% (leading tech firm), or 3.2% (founder/CEO) of each (Table 4, Panel A). This share is smallest for founder/CEO, also our least precise estimate ($p = 0.08$), so we are less confident that this association is robust. The conditional associations with field of work keep their sign against a confounder up to seven times as strong as IMO performance (Table 4, Panel B).

A more demanding benchmark is everything that is constant across countries of origin. A confounder as relevant as the 100 country fixed effects would reduce the associations with top-10 PhD and major prizes to 18.4 and 4.9pp, still large relative to sample means of 9% and 12%, but would erase those with industry outcomes (Appendix Table A.8, Panel A). This benchmark may be too extreme: the fixed effects absorb many country-level factors that can shape both top-10 attendance and career success, so it is hard to envision a single confounder this strong. Against three interpretable country characteristics instead—log GDP per capita, English-speaking share, and linguistic distance—the associations appear much more robust (Appendix Table A.8, Panel B).

The joint pattern of field sorting and prizes also constrains the confounder: since top-10 attendance predicts fewer people in academia *and* more prizes, a single unobserved trait would have to push its carriers out of academia while raising their prize output; a combination of traits could do so only if one moved people out of academia and another raised prize output among those who stay. Differences in income across origin countries are already controlled for and serve as a benchmark in the analysis above; family wealth within countries could still matter, but it would have to make students both leave academia and win more prizes.

5.4 Heterogeneity by Ability

Interacting university tier with IMO performance quartiles (Table 5), we find conditional correlations consistent with complementarity between ability and university rank in academic outcomes. Relative to universities outside the top 500, the top-10 PhD premium of universities ranked 11–500 rises from zero in the bottom performance quartile to 7pp in the top quartile ($p < 0.01$), and their prize premium from 5pp to 17pp ($p < 0.01$). Top-10 premia for academic outcomes are also largest in the top quartile, though less precisely estimated, as relatively few participants in the 1980–2005 cohorts attended top-10 universities. Even so, within the top quartile the top-10 premia exceed the 11–500 premia for both top-10 PhDs ($p < 0.01$) and prizes ($p = 0.04$). Industry outcomes follow a different pattern: the leading-tech-firm and founder/CEO premia peak in the intermediate ability quartiles.

These patterns suggest gains from assortative matching in scientific output among the world's top math talent, which contrasts with the existing literature on the assortative returns to college education. That literature focuses mostly on earnings returns for students well below the top of the ability distribution, using admission cutoffs or students' choices among colleges that admitted them as sources of identifying variation, and finds that the returns to attending a more selective college rise little, if at all, with prior achievement (Bleemer, 2022, 2024; Barahona et al., 2026; Mountjoy and Hickman, 2021); even at Ivy-Plus colleges, Chetty et al. (2026) cannot reject equal effects by test score, although their point estimate for the predicted probability of reaching the top 1% of earnings is largest for the highest scorers. Relying on selection on observables in a representative sample of US four-year college students, Dillon and Smith (2020) do find complementarity between ability and college quality in long-run earnings. None of these studies speaks to the comparison relevant for the undermatch we study here: between the world's top STEM talent and the marginal admits they would displace at top universities. That ability gap is likely far larger than the spread within IMO participants, so the complementarity we find even within this group is consistent with the undermatch carrying costs for science.

6 Possible Reasons for the Undermatch

This section examines four candidate explanations for why many medalists do not attend top universities: a taste for home, how universities read ability signals, admission odds, and financing.

6.1 Bounding the Taste for Home

Stated aspirations help bound how much of the undermatch home taste alone can explain. A survey of IMO participants from 2009–2018 (610 respondents from 76 countries; Agarwal et al. 2023; Agarwal et al. 2021, Figure 3) found that 81% of respondents from developing countries aspired to study in the US or UK, and only 11% in their home country. Among the full reference population in our data—developing-country participants 2009–2019—only 17% are found in a US or UK university, which should be close to the total share in those universities, given our validation exercise (Section 3.2.4). Among the survey respondents from developing countries, 31% actually studied in the US or UK, so, while the sample was biased towards more international students (with presumably much weaker home tastes), at least $81 - 31 = 50\%$ of those participants were studying outside the US or UK against their preferences.

6.2 Ability Signals

Top universities may use IMO medals—rather than the underlying scores—as signals of ability. Even if they do not, applicants may believe that they do, affecting their application decisions. We test for this friction with a regression discontinuity at each of the three medal cutoffs: bronze vs. no medal, silver vs. bronze, and gold vs. silver. For each year and medal tier, we define the cutoff as the midpoint between the highest score percentile among non-recipients and the lowest among recipients. The running variable is the signed gap between a participant's score percentile and the cutoff at their best attempt—the maximum of the per-year gaps across their

IMO participations, positive for those who cleared the cutoff and negative otherwise.[14]

For IMO cohorts 2006–2020, we cannot reject that top-10 attendance changes smoothly at the bronze and silver thresholds—estimates of 4.9pp (s.e. 4.5) and −3.4pp (s.e. 4.4)—and jumps at gold: 10.9pp (s.e. 5.0, $p = 0.03$), ranging from 9.2pp to 15.1pp across bandwidths (Figure 4). The jump at gold is as large for top-50 attendance and weaker for top-500 attendance (Appendix Figures A.3–A.4), and no medal effect appears in 1981–2005 (Appendix Figure A.2). The gold jump is not driven by data collection: gold medalists are no more likely than silver medalists to have an undergraduate institution in our data (0.4pp, s.e. 3.8; Appendix Figure A.5).

The relevance of a gold medal suggests that universities do not fully internalize the ability signal provided by IMO scores, or, at least, that medalists believe that to be the case. If bronze and silver medalists received the gold premium, top-10 placement would rise by roughly 9pp—about one-eighth of the gap between developing-country and US/UK medalists. The matching market may additionally under-use the continuous score signal itself (e.g., universities may under-value the signal that an intermediate IMO performance contains about ability), but we would need additional hypotheses about universities' preferences and applicants' beliefs to test that.

6.3 Admission Odds

Female medalists reach top universities far more often than male medalists with the same scores: 20–25pp higher top-10 attendance conditional on performance, origin, and cohort (all $p < 0.01$; Table 2). The premium is just as large among medalists whose country hosts no top-10 university (column 3)—students who can reach one only through an international application. Differences in home taste are an unlikely explanation: there is no evidence that female medalists are more eager than their male teammates to study abroad, and they would need to be far more

[14] A competitor who once placed two percentiles below silver and once three percentiles above shows up as barely getting silver, with running variable three. The bronze comparison excludes manually coded undergraduate institutions to avoid mechanical data-collection effects. Appendix Figure A.1 confirms that medal receipt jumps sharply at each cutoff.

eager to generate gaps of this size. A more plausible explanation is that universities admit female medalists at higher rates—an active admissions preference, plausibly for gender diversity in STEM.

Score-based screening supports the same conclusion. In the placement regressions, each percentile of IMO performance is associated with 0.3–0.4pp higher top-10 attendance (Table 2). Again, differences in home taste are unlikely to explain this positive association between math ability and placement: for preferences to generate this gradient, appetite for a top-10 education would have to rise steeply with contest score, and jump discontinuously at the silver–gold threshold, given the results of the previous section. Like the female premium, the gradient more plausibly reflects decisions made in admissions offices.

6.4 Financing, Aid, and Information

The sticker price of a four-year top-10 degree, roughly $360k including room and board, is prohibitive for most families outside wealthy countries. Nevertheless, strong applicants are often not charged sticker prices. Admission and aid policies vary widely across the top tier—some US privates disregard ability to pay in admission while others weigh it, and Oxford and Cambridge ask international offer holders to show they can fund the full course—but the price a student actually pays, net of aid, varies much less: most top US privates meet the demonstrated need of the international students they admit, so a poor medalist pays a small fraction of the sticker price; some Cambridge colleges award means-tested bursaries that can cover the full cost; ETH Zurich charges negligible tuition. The out-of-pocket cost, however, is resolved only after admission: applicants see the sticker and must guess at the aid, generating uncertainty that can deter applications (Hoxby and Avery, 2013; Hoxby and Turner, 2015; Dynarski et al., 2021). Among international students, uncertainty about a later stage also deters earlier steps: between 2004 and 2015, a higher expected student-visa refusal rate reduced SAT taking and score sending to US colleges, more so among high scorers (Chen et al., 2023).

Attendance is highest, and rising, at the top universities that combine favorable admission policies with generous funding. Figure 5 dates the improvement in the allocation to the late 2000s and shows that MIT and Cambridge, the two institutions that pair full funding for admitted internationals with admissions that actively value olympiad performance, account for most of it; they now enroll 21% of all 2015–2020 medalists. MIT admitted international students need-blind—ability to pay played no role in the admission decision—and Cambridge came close in practice: offers were made on academic grounds alone, and Trinity College, which enrolled many of its top mathematicians, awarded a limited number of its international offer-holders (eleven a year in 2018) means-tested Trinity Overseas Bursaries that could cover the full cost of attendance. For comparison, Harvard, Yale, Princeton, and Amherst—the other US colleges that admitted international students need-blind—together enrolled 46 medalists of these cohorts against MIT's 122. The availability of full funding alone does not attract medalists at that scale.

7 Discussion

The undermatch we document parallels settings where talent reallocation has large aggregate effects: declining occupational barriers for women and Black men explain 20–40% of US growth in output per person since 1960 (Hsieh et al., 2019), and the influx of émigré scientists from Nazi Germany raised patenting by US inventors in their fields by 31% (Moser et al., 2014). Because the outcomes we measure—frontier PhD training, scientific prizes, positions at leading technology firms, and firm creation—are channels through which talent generates returns beyond the individual, the undermatch documented here can represent a meaningful social cost. How could policymakers best address the undermatch?

Several policies may be considered. One is to expand need-based scholarships for students who meet excellence requirements. Several top universities (e.g., MIT, Harvard, Yale, and Princeton) already meet the full financial need of the international students they admit, yet the

undermatch persists, which suggests that these universities either fail to attract the most talented applicants or do not admit all of those who apply. Such funded seats are likely limited by admission policies.[15] Donors and governments could persuade or cooperate with universities to offer more funded seats to international students, but evidence from the United States suggests that funding may not move applications unless it is simple and certain (Hoxby and Avery, 2013; Hoxby and Turner, 2015; Dynarski et al., 2021). Hence, an effective response to the undermatch may include targeting information that facilitates applications or directly incentivizing applications to top universities.

Quantifying the mechanisms behind the undermatch (home taste, information frictions, cost misperceptions) is important to identify which policies would better address the undermatch. Nevertheless, as we do not observe application decisions, or students' perceptions of acceptance probabilities and application costs, our data cannot readily provide answers. As an exploratory exercise, we fully specify and estimate a model in which students make costly university application decisions, which allows us to simulate policy counterfactuals. The identification is based on strong assumptions about functional forms and about which factors affect attendance utility, costs, or acceptance probabilities; we provide full details in Appendix E.3. In summary, our estimates suggest that guaranteeing admission at the top-10 universities would raise top-10 enrollment more than removing the perceived one-time costs of entering the US and UK application systems, which in turn would do more than covering tuition and living costs. These findings are consistent with a story in which perceived acceptance probabilities are low and perceived application costs are high. A strategy that involves both universities—increasing acceptance probabilities to talented students—and application support may have the best chances to succeed.

[15] MIT limits admits of international students living abroad to 6% of its undergraduate admissions, which yields about 10% international students in each entering class (Massachusetts Institute of Technology, 2017). Stanford admits international applicants need-aware, with limited financial aid (Stanford University Office of Undergraduate Admission, 2026). The University of California offers international undergraduates no need-based aid (UC Berkeley Financial Aid and Scholarships Office, 2026) and caps nonresident (out-of-state and international) enrollment (University of California Office of the President, 2017).

Targeting such policies is not necessarily simple, either. Our presentation has focused on IMO medalists, a population for whom scores are strong predictors of later-life achievements, but top talent may be harder to spot in other domains. Even in math, not all top talent goes through the IMO. Among talented populations who cannot display a signal that is as widely recognized as the IMO, it is possible that there is much more undermatch, and such undermatch is harder to address, precisely because of the absence of strong signals. Signals also depend on opportunity: in the US, the arrival of a teacher who organizes math competitions more than doubles the number of top performers a school identifies (Calaway, 2026). One approach is to leverage scores from multiple international science olympiads (e.g., in physics, chemistry, and informatics), whose medalists win major science prizes at far higher rates than top-university graduates (Agarwal et al., 2025). Another is to test younger children with advanced material (like the SATs) (Lubinski and Benbow, 2006; Wai et al., 2005), but more research is needed to understand how to efficiently screen for talent.

8 Conclusion

Even among a population with access to widely legible ability signals, a large share of the very best talent around the world does not attend the universities that can best prepare it to contribute to society. If the science and innovation gains from assortative matching are real, this undermatch carries meaningful social costs. Several open questions remain, especially on how to identify talent that may benefit from funding and how best to support international university applications.

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Main Tables and Figures

Table 1: Descriptive Statistics for IMO 2015–2020 Medalists

Variable	Mean	Standard Deviation	Observations
UG not found	0.14	0.35	1,132
MIT or Cambridge	0.21	0.40	1,132
Top 10 university	0.29	0.45	1,132
Top 50 university	0.44	0.50	1,132
Top 500 university	0.75	0.43	1,132
Top 1000 university	0.79	0.41	1,132
Silver medal	0.35	0.48	1,132
Gold medal	0.19	0.40	1,132
Developing country	0.52	0.50	1,132
Low income	0.02	0.15	1,132
Lower-middle income	0.16	0.37	1,132
Upper-middle income	0.34	0.47	1,132
Female	0.06	0.23	1,132

Notes: This table reports summary statistics for IMO medalists whose last competition was in 2015–2020, including the US and UK. University indicators use the combined QS ranking (the better of the QS World and QS Mathematics 2020 ranks). Medalists whose undergraduate institution we could not find ("UG not found") are coded 0 on every university indicator, so those shares are lower bounds. Bronze-medal and high-income shares are not listed (complements of the rows shown). Developing countries are those not classified as high income by the World Bank.

Table 2: Predictors of University Placement (IMO 2015–2020 Medalists)

	Top 10 university			Top 50 university			Top 500 university		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Best Performance Percentile (0-100)	0.410***	0.350***	0.331***	0.353***	0.382***	0.285**	0.230*	0.240**	−0.022
	(0.117)	(0.096)	(0.098)	(0.131)	(0.113)	(0.129)	(0.132)	(0.097)	(0.260)
Female	19.560***	24.797***	24.910***	18.919***	22.961***	23.749***	12.783**	11.706**	19.030
	(6.029)	(5.919)	(6.089)	(5.926)	(5.836)	(6.784)	(5.114)	(4.827)	(15.218)
Has Domestic Top-k		59.874***			31.859***			21.727***	
		(4.959)			(3.795)			(4.071)	
Low / Lower-Middle Income		−7.821**	−7.774**		5.311	9.033**		−10.383***	−10.999
		(3.280)	(3.283)		(4.199)	(4.281)		(3.969)	(10.003)
Upper-Middle Income		1.204	1.269		5.673*	11.880***		−0.950	12.100
		(2.962)	(2.963)		(3.329)	(3.692)		(2.845)	(9.809)
Dep. var mean	28.89	28.89	26.02	43.73	43.73	35.94	75.35	75.35	54.42
Country FEs	Yes	No	No	Yes	No	No	Yes	No	No
Sample	All	All	No top-k	All	All	No top-k	All	All	No top-k
k	10	10	10	50	50	50	500	500	500
Observations	1,132	1,132	1,080	1,132	1,132	843	1,132	1,132	215
R^2	0.358	0.164	0.090	0.382	0.125	0.072	0.262	0.086	0.118

Notes: This table reports OLS estimates of linear probability models based on equation (3). The dependent variable is an indicator (×100) for attending a university at or above the indicated rank threshold (combined QS ranking: the better of the QS World and QS Mathematics 2020 ranks). All medalists are included; those whose undergraduate institution we could not find (14%) are coded as not attending, which understates attendance and likely biases the associations toward zero (Appendix Table A.6 restricts to medalists whose institution we found; the performance, gender, and domestic-access associations are generally the same or stronger there). "Has Domestic Top-k" equals one if the medalist's country hosts a university at or above the column's rank threshold k. Columns 3, 6, and 9 restrict the sample to medalists from countries without a domestic top-k university, so the indicator drops out. Income groups are World Bank classifications of the country of origin, collapsed to lower (low and lower-middle), upper-middle, and high; high income is the omitted group. Columns 1, 4, and 7 include country-of-origin fixed effects. All specifications include fixed effects for the number of IMO participations (capped at four) and the last-competition year. Robust (HC1) standard errors in parentheses; *p<0.1; **p<0.05; ***p<0.01.

Table 3: Career Outcomes, Field of Work, and University Tier

	Career success indicators (%)				Ever worked in		
	Top 10 PhD	Major prize	Leading tech firm	Founder/ CEO	Academia	Math	Finance
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Undergraduate university rank							
1–10	34.2***	16.6***	9.9***	4.9*	−6.7*	−6.5*	10.3***
	(3.4)	(3.4)	(2.5)	(2.8)	(3.6)	(3.5)	(2.7)
11–50	8.3***	9.7***	7.0***	−3.6*	−0.8	0.8	4.2**
	(2.3)	(2.6)	(1.8)	(2.1)	(3.1)	(3.2)	(2.1)
51–500	2.9**	9.9***	2.2**	−2.8*	1.7	4.5*	−0.5
	(1.4)	(1.9)	(1.1)	(1.7)	(2.3)	(2.4)	(1.4)
Not found	−5.5***	−11.3***	−3.0***	−11.0***	−45.9***	−21.1***	−6.0***
	(1.1)	(1.5)	(0.9)	(1.4)	(2.0)	(2.0)	(1.2)
Mean, rank >500 (omitted)	7.8	13.7	4.8	13.7	72.0	34.5	8.9
Mean, all participants	8.9	12.3	4.3	7.0	47.7	24.9	5.4
Observations	5,928	5,928	5,928	5,928	5,928	5,928	5,928
R^2	0.21	0.16	0.10	0.07	0.35	0.21	0.07

Notes: This table reports OLS estimates of equation (4), linear probability models of career outcomes (columns 1–4) and fields of work (columns 5–7) on the tier of the participant's undergraduate institution. Coefficients are in percentage points (outcomes $\times 100$), relative to an undergraduate institution ranked outside the top 500 in the combined QS ranking, including unranked institutions; "Mean, rank >500" is the outcome mean in this omitted group. Each field outcome equals one if the participant ever held a position in academia, mathematics, or finance (coded field of work and LinkedIn position histories). Sample: non-US/UK IMO participants whose last competition was in 2005 or earlier. Participants whose undergraduate institution we could not find (54%) are kept, with a "not found" indicator; field outcomes come from the same biographical sources, so its coefficients in columns 5–7 partly reflect missing career data. Appendix Table A.7 restricts the sample to participants whose institution we found. All columns control for a quadratic in the participant's best IMO score percentile, a female indicator, and fixed effects for country of origin, last-competition year, and number of IMO participations (capped at four). Robust (HC1) standard errors in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: Sensitivity to Unobserved Confounding

	Est.	$\text{RV}_{q=1}$	$\text{RV}_{q=1,\alpha=.05}$	IMO performance		
	(pp)			$1\times$	$3\times$	k_0
A. Career outcomes						
Top 10 PhD	34.2	19.6%	17.5%	33.7	32.7	63.3
Major prize	16.6	8.5%	6.1%	16.1	14.9	28.5
Leading tech firm	9.9	8.0%	5.6%	9.8	9.7	125.3
Founder/CEO	4.9	3.2%	0.7%	4.8	4.4	26.8
B. Field of work						
Academia	−6.7	2.6%	0.1%	−5.9	−4.2	8.1
Math	−6.5	2.7%	0.2%	−5.6	−3.7	7.0
Finance	10.3	7.3%	4.9%	10.1	9.8	62.0

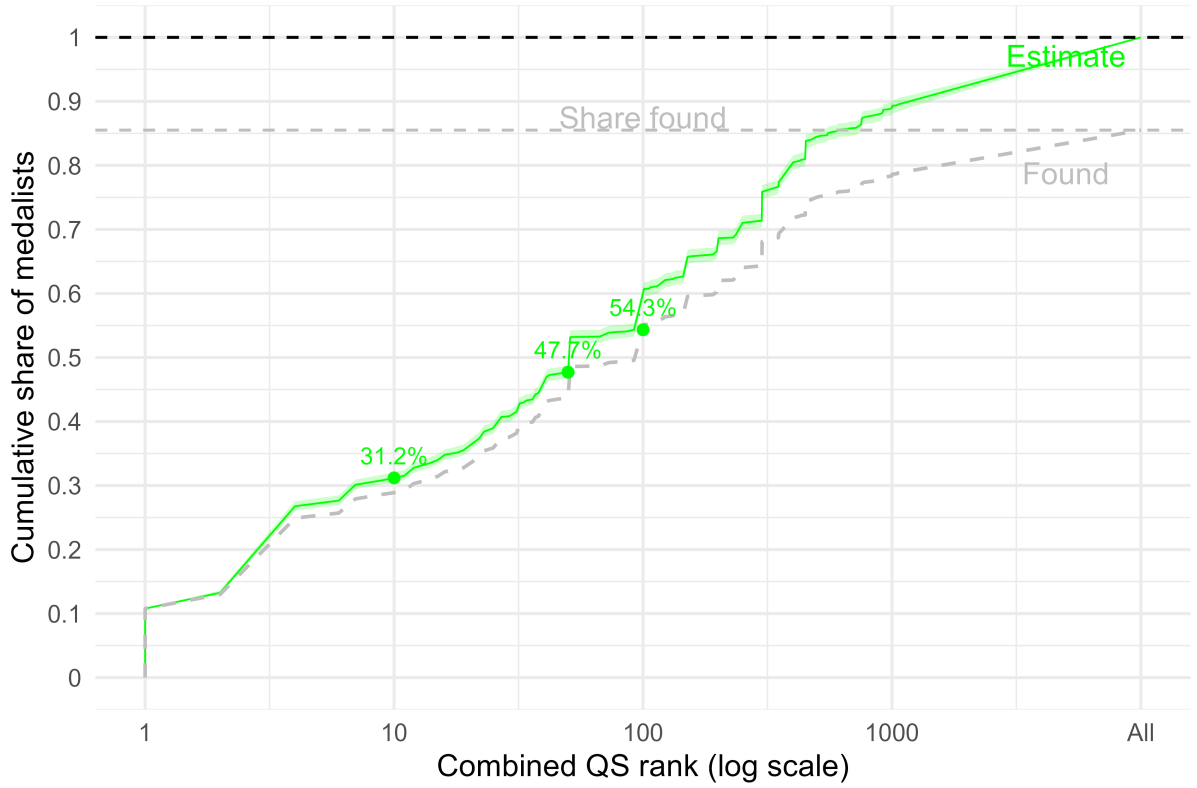
Notes: This table reports sensitivity statistics for the OLS estimate of the top-10 premium, following Cinelli and Hazlett (2020). Same sample as Table 3. Treatment: attended a top-10 university; the estimate is its premium over a university outside the top 500 (including unranked institutions). Controls: indicators for universities ranked 11–50 and 51–500, IMO performance (linear and quadratic), a female indicator, fixed effects for country of origin, fixed effects for last-competition year, a UG-not-found indicator, and fixed effects for the number of IMO participations (capped at four). Outcomes in percentage points. $\text{RV}_{q=1}$: robustness value — minimum partial R^2 of a confounder with both treatment and outcome needed to reduce the estimate to zero. $\text{RV}_{q=1,\alpha=.05}$: minimum needed to make the estimate insignificant at the 5% level (classical OLS standard errors). Benchmark columns: $1\times$ and $3\times$ give the bias-adjusted estimate if an unobserved confounder were 1 or 3 times as strongly associated with treatment and outcome as the benchmark; k_0 is the multiple of the benchmark's strength at which the adjusted estimate reaches zero. Benchmark: IMO performance (linear and quadratic, grouped).

Table 5: Tier Premia by IMO Performance Quartile

	Career success indicators (%)			
	Top 10 PhD	Major prize	Leading tech firm	Founder/ CEO
	(1)	(2)	(3)	(4)
Rank 1–10 × IMO score quartile				
75–100	43.2***	28.4***	7.8**	−0.1
	(5.2)	(5.3)	(3.9)	(3.5)
50–75	35.1***	13.2**	10.6**	5.9
	(6.7)	(6.2)	(4.7)	(5.4)
25–50	21.6***	2.5	18.0***	12.1*
	(6.6)	(5.4)	(5.8)	(6.2)
0–25	26.0***	14.0*	1.2	6.4
	(8.8)	(8.0)	(4.4)	(7.1)
Rank 11–500 × IMO score quartile				
75–100	7.5***	17.4***	3.9**	−4.6**
	(2.2)	(2.6)	(1.6)	(1.8)
50–75	3.7*	7.2***	3.9***	−2.2
	(2.0)	(2.5)	(1.5)	(2.1)
25–50	3.1*	6.7***	3.6**	−4.1*
	(1.8)	(2.6)	(1.5)	(2.3)
0–25	0.3	4.8*	1.0	−0.1
	(1.9)	(2.8)	(1.6)	(2.5)
Not found	−5.8***	−11.5***	−3.0***	−10.9***
	(1.1)	(1.5)	(0.9)	(1.4)
Mean, all participants	8.9	12.3	4.3	7.0
Observations	5,928	5,928	5,928	5,928
R^2	0.21	0.17	0.10	0.07

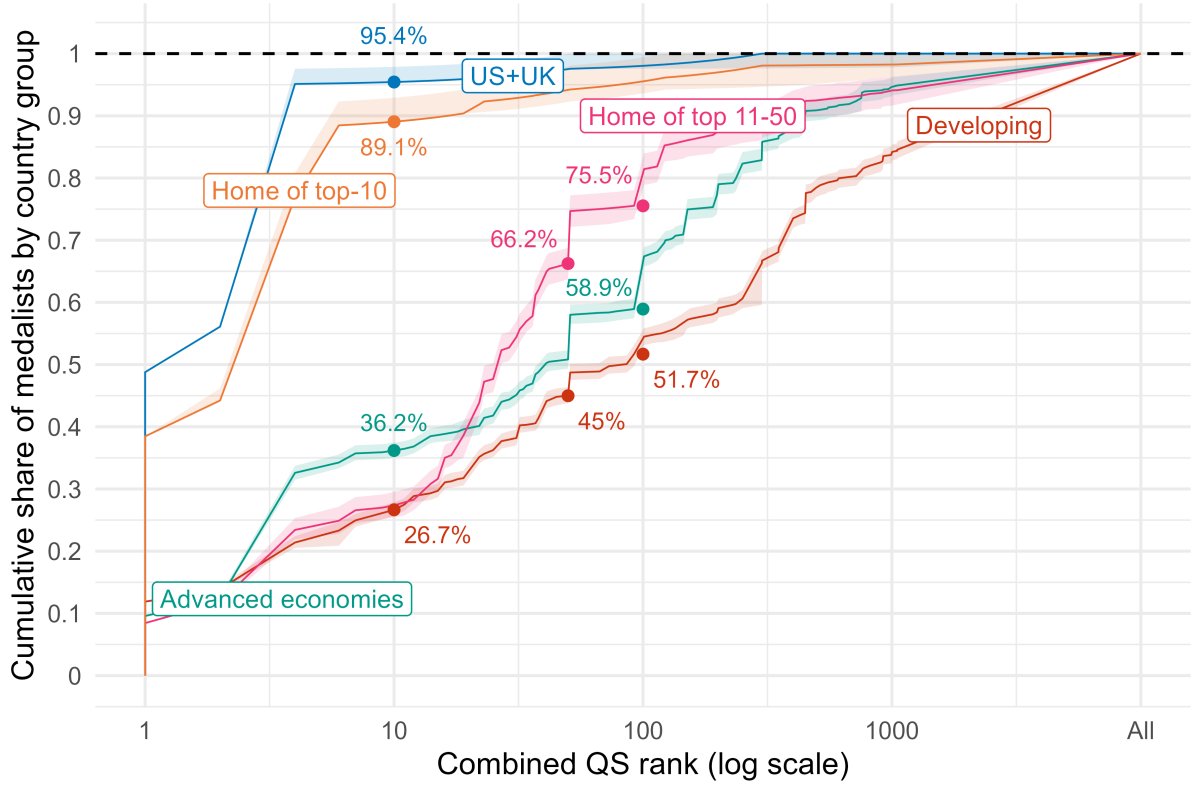
Notes: This table reports OLS estimates of a version of equation (4) that interacts university tier with the participant's IMO score-percentile quartile (0–25, 25–50, 50–75, 75–100). Each coefficient is the premium of a top-10 university, or of a university ranked 11–500, over one outside the top 500, for participants in that quartile, in percentage points (outcomes ×100). Sample: non-US/UK IMO participants whose last competition was in 2005 or earlier. Participants whose undergraduate institution we could not find are kept, with a "not found" indicator; Appendix Table A.9 restricts the sample to participants whose institution we found. All columns control for a quadratic in the participant's best IMO score percentile, quartile indicators, a female indicator, and fixed effects for country of origin, last-competition year, and number of IMO participations (capped at four). Robust (HC1) standard errors in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure 1: Cumulative Share of Medalists by University Rank



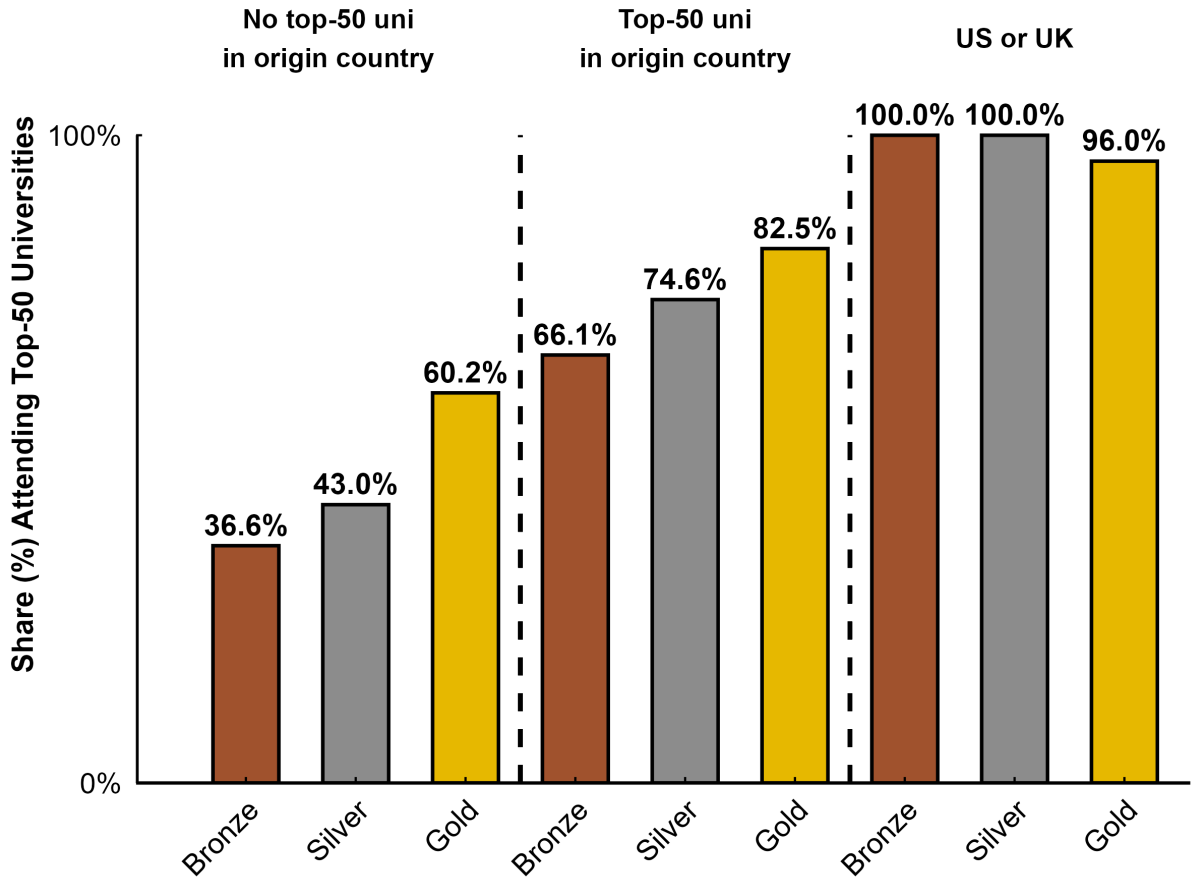
Notes: Cumulative share of IMO medalists (2015–2020, $N = 1{,}132$) attending a university at or above each combined QS rank (the better of the QS World and QS Mathematics 2020 rankings; see Section 3). Dashed curve: observed allocation of medalists whose undergraduate institution we found, as a share of all 1,132 medalists. Solid curve: median estimated allocation from 1,000 simulation draws, where each missing medalist is assigned to a university rank with probability proportional to the estimated gap between observed and expected enrollment at that rank (see text). Shaded area: 2.5th–97.5th percentiles across draws (simulation band; it reflects only the randomness of the imputation). "All" includes institutions without a QS rank. The horizontal dashed line marks the share of medalists whose institution we found (85.5%). Percentage annotations show the median cumulative share at the top-10, top-50, and top-100 thresholds.

Figure 2: Cumulative Share of Medalists by University Rank and Origin-Country Group



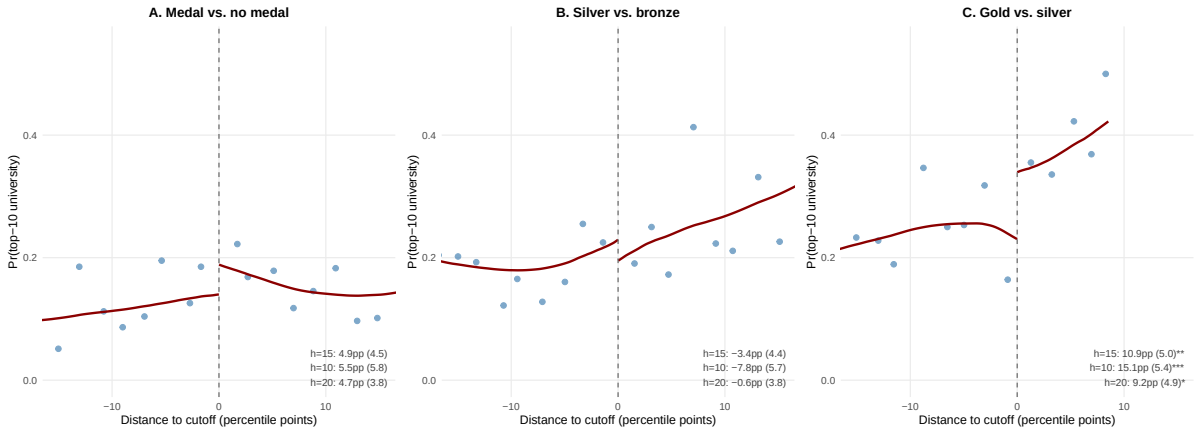
Notes: Cumulative estimated share of IMO medalists (2015–2020, $N = 1{,}132$) attending a university at or above each combined QS rank, by origin country group. Solid lines: median allocation from 1,000 simulation draws (see Figure 1 notes); shaded areas: simulation bands (2.5th–97.5th percentiles across draws). "Developing" ($n = 589$): non-high-income economies per World Bank classification; "Advanced economies" ($n = 543$): high-income countries. "US+UK" ($n = 41$): medalists from the United States or United Kingdom. "Home of top-10" ($n = 52$): medalists from countries hosting a top-10 university in the combined ranking (US, UK, Switzerland); "Home of top 11–50" ($n = 237$): countries hosting a top-50 but no top-10 university. The two access groups are mutually exclusive, and "US+UK" is a subset of "Home of top-10"; they overlap with the income groups (e.g., China is both "Home of top 11–50" and "Developing"). Percentage annotations show cumulative shares at the top-10, top-50, and top-100 thresholds for "Developing", at the top-50 and top-100 thresholds for "Home of top 11–50", at the top-10 and top-100 thresholds for "Advanced economies", and at the top-10 threshold for "Home of top-10" and "US+UK".

Figure 3: Country of Origin Matters More Than Medals



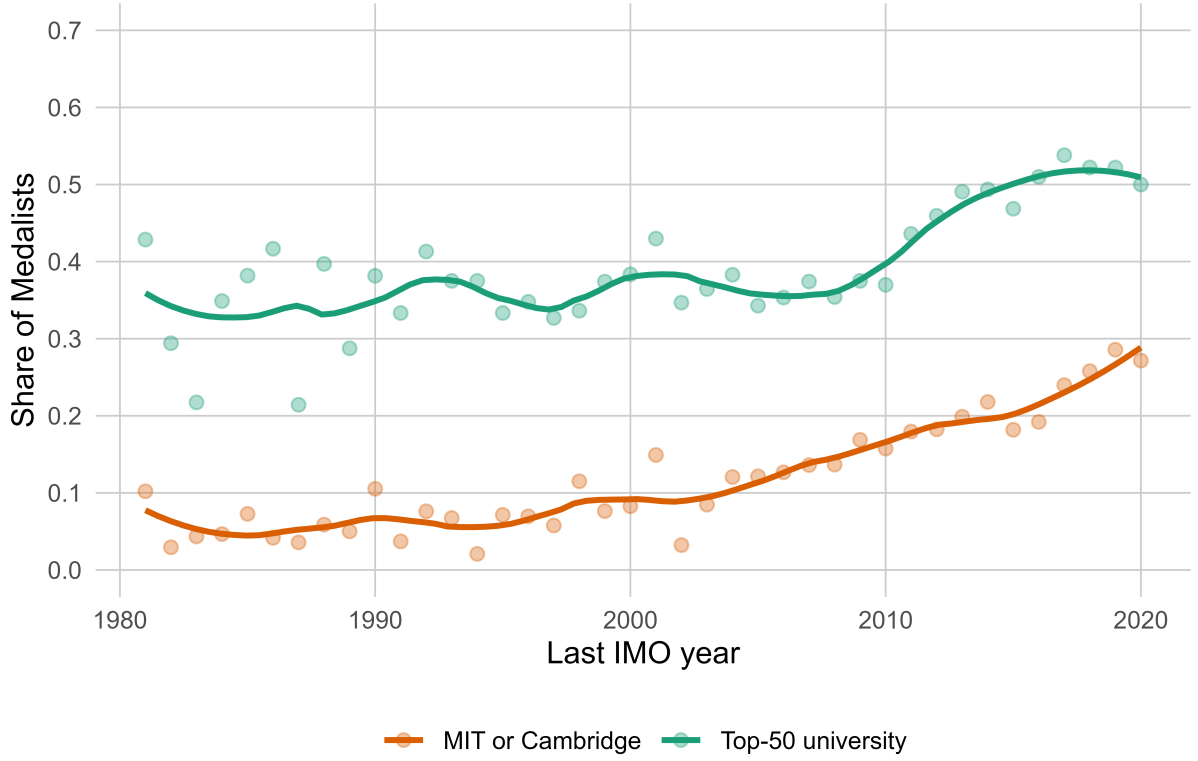
Notes: Share of IMO medalists (2015–2020) attending a top-50 university (combined QS ranking), by best IMO medal and origin country group. Sample restricted to medalists with UG found ($N = 968$). Three mutually exclusive groups: "No top-50 uni in origin country" ($n = 725$) denotes medalists from countries without a top-50 university; "Top-50 uni in origin country" ($n = 203$) denotes medalists from countries hosting at least one top-50 university, excluding US and UK; "US or UK" ($n = 40$: 25 gold, 11 silver, and 4 bronze medalists), so its bars rest on few observations. Unlike the groups of Figure 2, the top-50 group includes Switzerland.

Figure 4: Regression Discontinuity at Medal Cutoffs: Effect on Top-10 University Attendance



Notes: Regression discontinuity estimates at each IMO medal cutoff. The outcome is attending a top-10 university (combined QS ranking). Each panel plots binned means (2-percentile-point bins) and a local linear fit (triangular kernel) within a fixed bandwidth of 15 percentile points on each side of the cutoff; annotations report estimates (s.e.) at bandwidths of 15, 10, and 20 points. The running variable is the participant's score percentile minus the year-specific medal threshold, in percentile points, taken from the participation in which this difference is largest; the threshold is the midpoint between the highest percentile of non-recipients and the lowest percentile of recipients. Conventional point estimates and standard errors from `rdrobust` (Calonico et al., 2014). Panel A uses all participants whose last IMO was in 2006–2020 ($N = 5{,}292$), with university data from automated sources only, since manual coding covers medalists only; panels B and C use the medalist sample ($N = 2{,}750$), with manually coded institutions. Participants whose institution we could not find are coded as not attending; Appendix Figure A.5 shows that finding an institution does not jump at the cutoffs. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure 5: Top-University Attendance Has Risen Since the 2000s

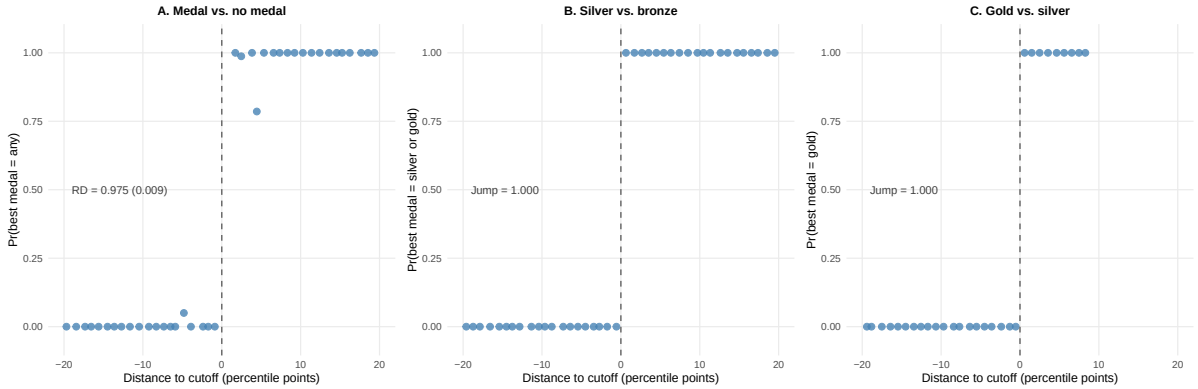


Notes: Share of IMO medalists attending a top-50 university in the combined QS ranking or MIT/Cambridge specifically, by last year of IMO participation (1981–2020). Sample restricted to medalists with UG found. Points show annual shares; curves are loess-smoothed (span = 0.3). The MIT/Cambridge share rises from the mid-2000s; the top-50 share is flat at about 35% until around 2010 and exceeds 50% in 2016–2020.

Appendices

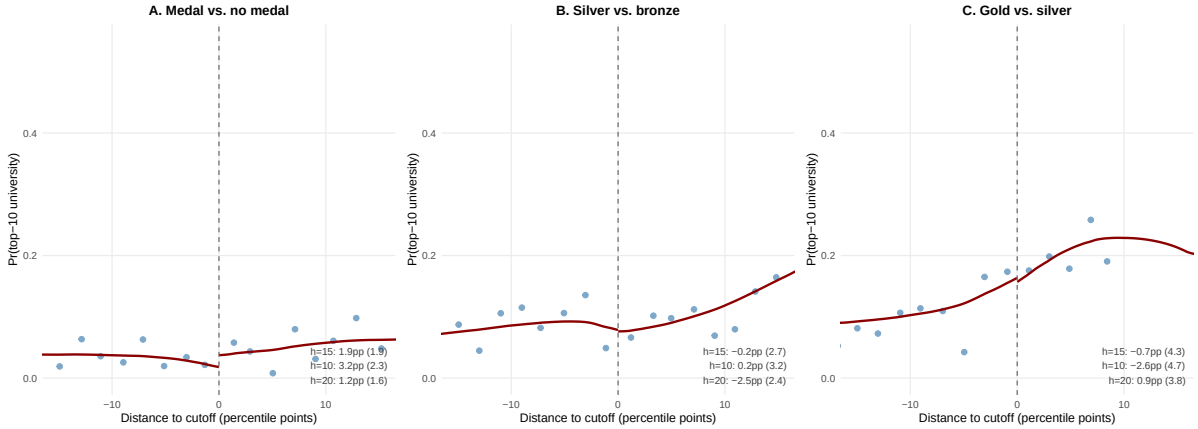
A Additional Figures

Figure A.1: First Stage: Medal Receipt at Each Cutoff



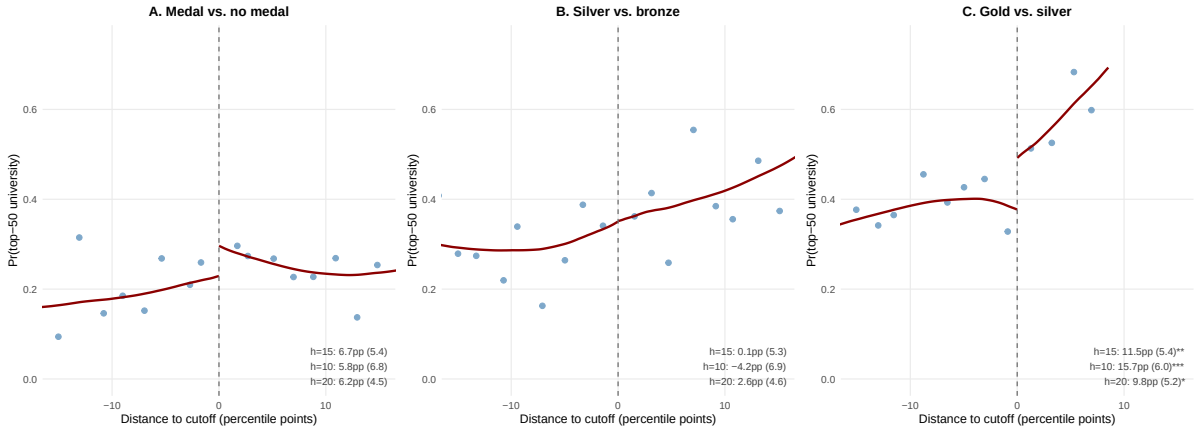
Notes: First-stage regression discontinuity plots showing that medal receipt jumps sharply at each cutoff. The outcome is an indicator for receiving the relevant medal (or better). The running variable is the participant's score percentile minus the year-specific medal threshold, in percentile points, taken from the participation in which this difference is largest. Binned means (1-percentile-point bins) within 20 points of the cutoff. Panel A reports the bias-corrected robust `rdrobust` estimate at the MSE-optimal bandwidth; panels B and C report the raw difference in means, since separation is perfect. Panel A: any medal vs. no medal. Panel B: silver or gold vs. bronze. Panel C: gold vs. silver. All three thresholds produce near-perfect first stages. Sample: all participants whose last IMO was in 2006–2020 (all three panels).

Figure A.2: Regression Discontinuity at Medal Cutoffs: 1981–2005 Cohort



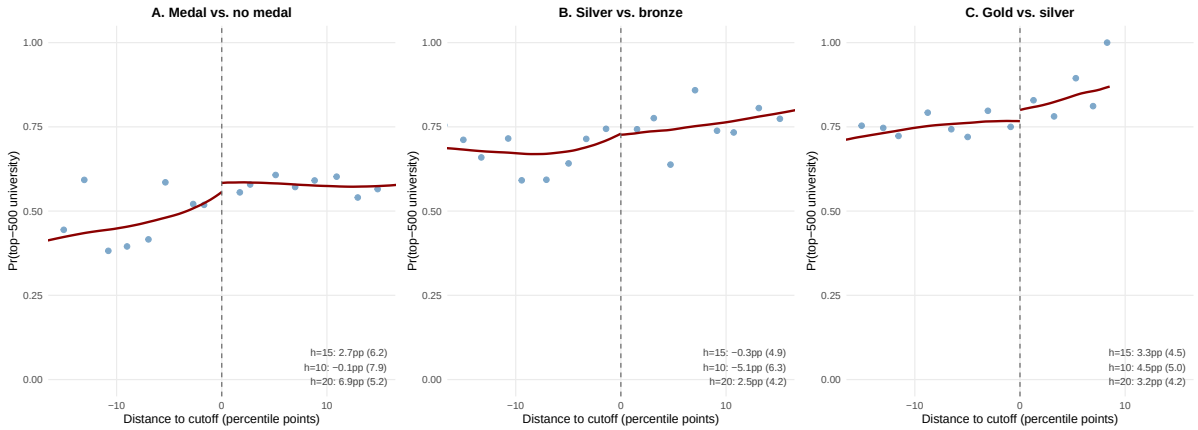
Notes: Same specification as Figure 4 but for participants whose last IMO was in 1981–2005 (panel A: $N = 6{,}132$ participants; panels B and C: $N = 3{,}034$ medalists). None of the three RD estimates is significant: 1.9pp (s.e. 1.9) for any medal, −0.2pp (s.e. 2.7) for silver, and −0.7pp (s.e. 4.3) for gold.

Figure A.3: Regression Discontinuity at Medal Cutoffs: Top-50 University



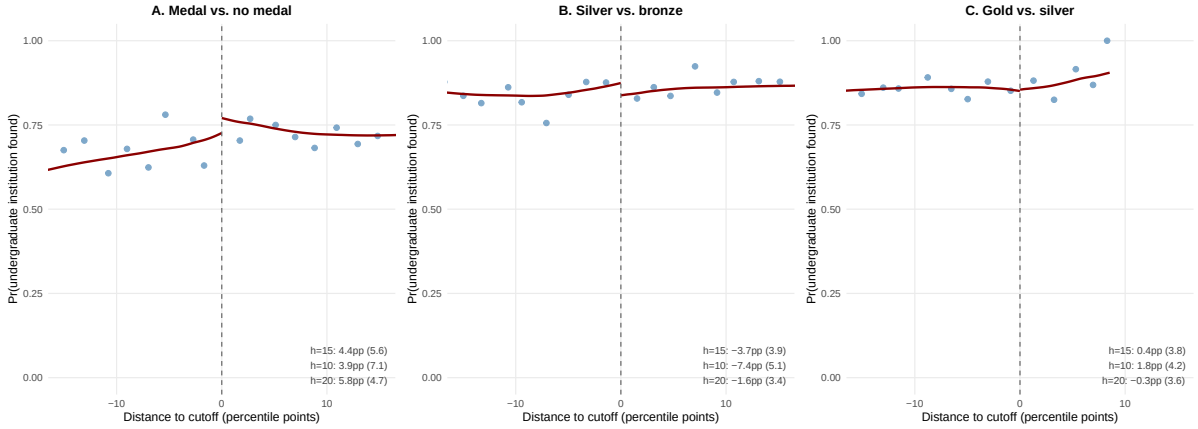
Notes: Same specification as Figure 4 but with attending a top-50 university as the outcome.

Figure A.4: Regression Discontinuity at Medal Cutoffs: Top-500 University



Notes: Same specification as Figure 4 but with attending a top-500 university as the outcome.

Figure A.5: Regression Discontinuity at Medal Cutoffs: Undergraduate Institution Found



Notes: Same specification as Figure 4 but with finding any undergraduate institution as the outcome. None of the three RD estimates is significant at any bandwidth.

B Additional Tables

Table A.1: Universities Classified as "Top 10" and "Top 11–50" (Combined QS 2020 Ranking)

University	Cty.	World	Math	Comb.	University	Cty.	World	Math	Comb.
A. Top 10 (14 universities)					*B. Top 11–50 (continued)*				
Massachusetts Institute of Technology	USA	1	1	1	Duke University	USA	25	51	25
Stanford University	USA	2	3	2	University of Hong Kong	HKG	26	43	26
Harvard University	USA	3	2	2	The University of Texas at Austin	USA	65	26	26
University of Oxford	GBR	4	5	4	University of Manchester	GBR	27	51	27
University of Cambridge	GBR	7	4	4	Carnegie Mellon University	USA	48	27	27
California Institute of Technology	USA	5	17	5	École Polytechnique	FRA	60	27	27
ETH Zurich	CHE	6	8	6	Sorbonne Université	FRA	76	27	27
University of California, Berkeley	USA	28	6	6	Australian National University	AUS	29	39	29
Princeton University	USA	13	7	7	Georgia Institute of Technology	USA	72	30	30
University College London	GBR	8	49	8	Northwestern University	USA	31	51	31
Imperial College London	GBR	9	11	9	Chinese University of Hong Kong	HKG	46	31	31
University of California, Los Angeles	USA	36	9	9	Hong Kong University of Science and Technology	HKG	32	34	32
University of Chicago	USA	10	16	10	The University of Melbourne	AUS	38	32	32
New York University	USA	39	10	10	King's College London	GBR	33	51	33
B. Top 11–50 (49 universities)					Kyoto University	JPN	34	49	34
Nanyang Technological University	SGP	11	49	11	McGill University	CAN	35	51	35
National University of Singapore	SGP	12	13	12	UNSW Sydney	AUS	43	36	36
Columbia University	USA	18	12	12	Seoul National University	KOR	37	47	37
Cornell University	USA	14	33	14	KTH Royal Institute of Technology	SWE	99	38	38
Université Paris Sciences et Lettres	FRA	53	14	14	Shanghai Jiao Tong University	CHN	61	39	39
University of Pennsylvania	USA	15	34	15	Fudan University	CHN	40	49	40
University of Toronto	CAN	30	15	15	Korea Advanced Institute of Science and Technology	KOR	41	51	41
Tsinghua University	CHN	16	20	16	University of Waterloo	CAN	176	41	41
Yale University	USA	17	21	17	The University of Sydney	AUS	42	45	42
University of Michigan	USA	21	18	18	Brown University	USA	57	42	42
École Polytechnique Fédérale de Lausanne	CHE	19	24	19	Lomonosov Moscow State University	RUS	85	43	43
University of Warwick	GBR	62	19	19	London School of Economics and Political Science	GBR	44	101	44
University of Edinburgh	GBR	20	36	20	University of California San Diego	USA	45	47	45
Peking University	CHN	22	22	22	University of Wisconsin–Madison	USA	56	45	45
The University of Tokyo	JPN	23	24	23	The University of Queensland	AUS	47	51	47
University of British Columbia	CAN	51	23	23	University of Bristol	GBR	49	51	49
Johns Hopkins University	USA	24	51	24	Delft University of Technology	NLD	50	51	50

Notes: This table lists the universities with a combined QS rank (the better of their QS World 2020 and QS Mathematics 2020 ranks) of 50 or better. Tied combined ranks put 14 universities in the top-10 tier. QS Mathematics ranks below 50 are published in bands; we use the top of the band (e.g., 51 for 51–100). Constituent institutions take their parent university's rank (e.g., École Normale Supérieure takes PSL's). Cty.: ISO country code.

Table A.2: What Predicts a Missing Undergraduate Institution (IMO 1981–2020 Medalists)

	UG not found	
	(1)	(2)
Best Performance Percentile (0-100)	-0.254^{***}	-0.195^{***}
	(0.047)	(0.037)
Female	-3.598	-3.491
	(2.202)	(2.169)
Low / Lower-Middle Income		3.651^{***}
		(1.269)
Upper-Middle Income		-3.715^{***}
		(1.200)
Last IMO Year (linear trend)	-0.604^{***}	-0.486^{***}
	(0.053)	(0.052)
Dep. var mean	19.78	19.78
Country FEs	Yes	No
Observations	5,784	5,784
R^2	0.133	0.041

Notes: This table reports OLS estimates of linear probability models on all 1981–2020 medalists. The dependent variable is an indicator ($\times 100$) for not finding the medalist's undergraduate institution from any source. Covariates follow Table 2, except that the domestic top-k indicator is omitted and the last competition year enters linearly rather than as fixed effects, so its coefficient is the trend in the miss rate (percentage points per year). Income groups are World Bank classifications of the country of origin, collapsed to lower (low and lower-middle), upper-middle, and high; high income is the omitted group. Column 1 replaces the income groups with country-of-origin fixed effects. Both specifications include fixed effects for the number of IMO participations (capped at four). Robust (HC1) standard errors in parentheses; *p<0.1; **p<0.05; ***p<0.01.

Table A.3: Descriptive Statistics for IMO 1981–2000 and 2001–2014 Medalists

	1981–2000		2001–2014	
Variable	Mean	SD	Mean	SD
UG not found	0.27	0.44	0.16	0.36
MIT or Cambridge	0.05	0.22	0.12	0.33
Top 10 university	0.10	0.30	0.20	0.40
Top 50 university	0.26	0.44	0.34	0.47
Top 500 university	0.62	0.49	0.71	0.45
Top 1000 university	0.67	0.47	0.75	0.44
Silver medal	0.34	0.47	0.34	0.47
Gold medal	0.18	0.39	0.21	0.40
Developing country	0.58	0.49	0.57	0.49
Low income	0.12	0.32	0.07	0.25
Lower-middle income	0.27	0.44	0.24	0.43
Upper-middle income	0.20	0.40	0.26	0.44
Female	0.04	0.21	0.06	0.23
Observations	2,252		2,400	

Notes: This table reports summary statistics for IMO medalists whose last competition was in 1981–2000 or 2001–2014, including the US and UK. University indicators use the combined QS ranking (the better of the QS World and QS Mathematics 2020 ranks, applied to all cohorts). Medalists whose undergraduate institution we could not find ("UG not found") are coded 0 on every university indicator, so those shares are lower bounds. Bronze-medal and high-income shares are not listed (complements of the rows shown). Developing countries are those not classified as high income by the World Bank.

Table A.4: Predictors of University Placement (IMO 1981–2000 Medalists)

	Top 10 university			Top 50 university			Top 500 university		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Best Performance Percentile (0-100)	−0.011	0.017	−0.013	0.179***	0.300***	0.236***	0.405***	0.492***	0.132
	(0.042)	(0.036)	(0.032)	(0.064)	(0.057)	(0.060)	(0.084)	(0.068)	(0.155)
Female	3.074	1.926	2.250	9.592***	6.599*	3.142	10.226**	9.106*	20.215**
	(2.775)	(2.897)	(2.751)	(3.341)	(3.948)	(4.278)	(4.591)	(4.690)	(9.311)
Has Domestic Top-*k*		59.906***			48.751***			30.455***	
		(3.833)			(2.240)			(2.644)	
Low / Lower-Middle Income		−0.010	−0.015		1.620	8.039***		−13.809***	−11.900
		(1.136)	(1.125)		(1.893)	(1.778)		(2.335)	(8.163)
Upper-Middle Income		−0.352	−0.305		−0.320	3.335*		−3.974	12.288
		(1.344)	(1.339)		(2.055)	(1.890)		(2.790)	(8.347)
Dep. var mean	9.77	9.77	5.50	25.84	25.84	11.19	61.90	61.90	34.05
Country FEs	Yes	No	No	Yes	No	No	Yes	No	No
Sample	All	All	No top-*k*	All	All	No top-*k*	All	All	No top-*k*
k	10	10	10	50	50	50	500	500	500
Observations	2,252	2,252	2,090	2,252	2,252	1,582	2,252	2,252	464
R^2	0.389	0.293	0.043	0.429	0.289	0.050	0.263	0.130	0.127

Notes: This table reports OLS estimates of linear probability models based on equation (3). The dependent variable is an indicator (×100) for attending a university at or above the indicated rank threshold (combined QS ranking: the better of the QS World and QS Mathematics 2020 ranks). All medalists of the period are included; those whose undergraduate institution we could not find (27%) are coded as not attending, which understates attendance and likely biases the associations toward zero. "Has Domestic Top-*k*" equals one if the medalist's country hosts a university at or above the column's rank threshold *k*. Columns 3, 6, and 9 restrict the sample to medalists from countries without a domestic top-*k* university, so the indicator drops out. Income groups are World Bank classifications of the country of origin, collapsed to lower (low and lower-middle), upper-middle, and high; high income is the omitted group. Columns 1, 4, and 7 include country-of-origin fixed effects. All specifications include fixed effects for the number of IMO participations (capped at four) and the last-competition year. Robust (HC1) standard errors in parentheses; *p<0.1; **p<0.05; ***p<0.01.

Table A.5: Predictors of University Placement (IMO 2001–2014 Medalists)

	Top 10 university			Top 50 university			Top 500 university		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Best Performance Percentile (0-100)	0.254***	0.327***	0.307***	0.353***	0.316***	0.273***	0.228***	0.307***	0.269
	(0.069)	(0.055)	(0.056)	(0.078)	(0.067)	(0.074)	(0.084)	(0.064)	(0.189)
Female	9.068***	10.705***	9.901***	7.047**	7.615**	8.614**	2.542	5.088	8.272
	(3.159)	(3.522)	(3.643)	(3.509)	(3.871)	(4.320)	(3.295)	(3.563)	(9.573)
Has Domestic Top-k		58.197***			48.969***			33.300***	
		(4.086)			(2.460)			(2.858)	
Low / Lower-Middle Income		−1.783	−1.485		9.410***	13.068***		−8.090***	10.577
		(1.812)	(1.817)		(2.201)	(2.329)		(2.406)	(8.385)
Upper-Middle Income		−0.095	−0.092		4.079*	7.705***		−3.821*	15.526*
		(1.937)	(1.934)		(2.238)	(2.337)		(2.140)	(8.869)
Dep. var mean	19.67	19.67	16.56	33.67	33.67	21.49	70.79	70.79	39.87
Country FEs	Yes	No	No	Yes	No	No	Yes	No	No
Sample	All	All	No top-k	All	All	No top-k	All	All	No top-k
k	10	10	10	50	50	50	500	500	500
Observations	2,400	2,400	2,277	2,400	2,400	1,764	2,400	2,400	449
R^2	0.344	0.170	0.070	0.426	0.233	0.097	0.277	0.133	0.089

Notes: This table reports OLS estimates of linear probability models based on equation (3). The dependent variable is an indicator (×100) for attending a university at or above the indicated rank threshold (combined QS ranking: the better of the QS World and QS Mathematics 2020 ranks). All medalists of the period are included; those whose undergraduate institution we could not find (16%) are coded as not attending, which understates attendance and likely biases the associations toward zero. "Has Domestic Top-k" equals one if the medalist's country hosts a university at or above the column's rank threshold k. Columns 3, 6, and 9 restrict the sample to medalists from countries without a domestic top-k university, so the indicator drops out. Income groups are World Bank classifications of the country of origin, collapsed to lower (low and lower-middle), upper-middle, and high; high income is the omitted group. Columns 1, 4, and 7 include country-of-origin fixed effects. All specifications include fixed effects for the number of IMO participations (capped at four) and the last-competition year. Robust (HC1) standard errors in parentheses; *p<0.1; **p<0.05; ***p<0.01.

Table A.6: Predictors of University Placement (IMO 2015–2020 Medalists, UG Found Only)

	Top 10 university			Top 50 university			Top 500 university		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Best Performance Percentile (0-100)	0.459***	0.396***	0.399***	0.422***	0.399***	0.348**	0.230**	0.247***	0.266
	(0.131)	(0.108)	(0.112)	(0.137)	(0.124)	(0.143)	(0.104)	(0.077)	(0.298)
Female	20.599***	27.637***	28.138***	18.892***	24.040***	27.515***	11.613***	10.452***	30.292**
	(6.515)	(6.238)	(6.432)	(6.100)	(5.895)	(6.900)	(3.523)	(3.012)	(12.183)
Has Domestic Top-k		59.403***			38.041***			21.509***	
		(4.504)			(4.013)			(4.079)	
Low / Lower-Middle Income		−9.551**	−9.482**		6.466	11.459**		−14.201***	−0.580
		(3.823)	(3.826)		(4.701)	(4.803)		(3.545)	(10.411)
Upper-Middle Income		−0.909	−0.845		3.001	12.485***		−6.763***	18.036*
		(3.343)	(3.346)		(3.637)	(4.078)		(2.257)	(10.051)
Dep. var mean	33.78	33.78	30.58	51.14	51.14	41.79	88.12	88.12	65.00
Country FEs	Yes	No	No	Yes	No	No	Yes	No	No
Sample	All	All	No top-k	All	All	No top-k	All	All	No top-k
k	10	10	10	50	50	50	500	500	500
Observations	968	968	919	968	968	725	968	968	180
R^2	0.380	0.172	0.096	0.458	0.157	0.077	0.354	0.160	0.100

Notes: This table reports OLS estimates of linear probability models based on equation (3). The dependent variable is an indicator ($\times 100$) for attending a university at or above the indicated rank threshold (combined QS ranking: the better of the QS World and QS Mathematics 2020 ranks). Sample restricted to medalists whose undergraduate institution we found. "Has Domestic Top-k" equals one if the medalist's country hosts a university at or above the column's rank threshold k. Columns 3, 6, and 9 restrict the sample to medalists from countries without a domestic top-k university, so the indicator drops out. Income groups are World Bank classifications of the country of origin, collapsed to lower (low and lower-middle), upper-middle, and high; high income is the omitted group. Columns 1, 4, and 7 include country-of-origin fixed effects. All specifications include fixed effects for the number of IMO participations (capped at four) and the last-competition year. Robust (HC1) standard errors in parentheses; *p<0.1; **p<0.05; ***p<0.01.

Table A.7: Career Outcomes, Field of Work, and University Tier, UG Found Only

	Career success indicators (%)				Ever worked in		
	Top 10 PhD	Major prize	Leading tech firm	Founder/ CEO	Academia	Math	Finance
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Undergraduate university rank							
1–10	30.8***	15.1***	9.3***	5.9*	−4.6	−4.9	12.3***
	(3.8)	(3.7)	(2.7)	(3.1)	(3.9)	(3.9)	(3.0)
11–50	7.6**	8.1**	8.9***	−5.4**	4.4	1.9	5.6**
	(3.1)	(3.3)	(2.2)	(2.8)	(3.7)	(3.8)	(2.5)
51–500	1.5	6.6***	2.7**	−1.1	4.7*	3.5	2.9*
	(1.7)	(2.4)	(1.3)	(2.0)	(2.6)	(2.8)	(1.7)
Mean, rank >500 (omitted)	7.8	13.7	4.8	13.7	72.0	34.5	8.9
Mean, all participants	16.6	23.9	8.1	11.9	75.9	40.1	9.3
Observations	2,705	2,705	2,705	2,705	2,705	2,705	2,705
R^2	0.22	0.10	0.12	0.08	0.15	0.16	0.09

Notes: This table reports OLS estimates of the specification of Table 3, without the "not found" indicator, for the 2,705 participants (46%) whose undergraduate institution we found. Robust (HC1) standard errors in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.8: Sensitivity to Unobserved Confounding: Country of Origin as Benchmark

	Est.	$RV_{q=1}$	$RV_{q=1,\alpha=.05}$	Country benchmark		
	(pp)			1×	3×	k_0
A. Country fixed effects						
Top 10 PhD	34.2	19.6%	17.5%	18.4	—	2.0
Major prize	16.6	8.5%	6.1%	4.9	—	1.4
Leading tech firm	9.9	8.0%	5.6%	0.3	—	1.0
Founder/CEO	4.9	3.2%	0.7%	—	—	0.5
Academia	−6.7	2.6%	0.1%	—	—	0.3
Math	−6.5	2.7%	0.2%	—	—	0.3
Finance	10.3	7.3%	4.9%	1.7	—	1.2
B. Country characteristics						
Top 10 PhD	37.1	21.3%	19.2%	36.0	33.9	26.8
Major prize	15.7	8.3%	5.9%	15.2	14.2	24.8
Leading tech firm	10.0	8.2%	5.8%	9.5	8.3	15.9
Founder/CEO	4.3	2.9%	0.3%	3.7	2.5	7.1
Academia	−11.5	4.6%	2.1%	−8.1	−1.1	3.3
Math	−11.1	4.6%	2.2%	−8.5	−3.1	4.1
Finance	9.9	7.2%	4.8%	9.3	8.2	15.7

Notes: This table reports the sensitivity statistics of Table 4 with country of origin, instead of IMO performance, as the benchmark. Panel A: specification of Table 4; benchmark: the country fixed effects (grouped). Panel B: the country fixed effects are replaced by three country characteristics (log GDP per capita, English-speaking share, linguistic distance); benchmark: the three characteristics (grouped). In each panel, the first four rows are career outcomes and the last three fields of work. Outcomes in percentage points. 1× and 3× give the bias-adjusted estimate if an unobserved confounder were 1 or 3 times as strongly associated with treatment and outcome as the benchmark; k_0 is the multiple of the benchmark's strength at which the adjusted estimate reaches zero; — marks multiples above k_0.

Table A.9: Tier Premia by IMO Performance Quartile, UG Found Only

	Career success indicators (%)			
	Top 10 PhD	Major prize	Leading tech firm	Founder/ CEO
	(1)	(2)	(3)	(4)
Rank 1–10 × IMO score quartile				
75–100	37.2***	23.7***	5.3	5.2
	(6.1)	(6.4)	(4.4)	(4.2)
50–75	32.5***	11.5	10.6**	6.4
	(7.3)	(7.1)	(5.0)	(6.0)
25–50	18.8***	1.7	19.0***	8.8
	(7.1)	(6.2)	(6.1)	(6.9)
0–25	23.0**	17.2**	−0.5	7.0
	(9.5)	(8.5)	(5.3)	(7.6)
Rank 11–500 × IMO score quartile				
75–100	3.2	10.2**	2.9	0.7
	(3.6)	(4.5)	(2.9)	(2.9)
50–75	3.1	5.0	5.6**	−2.3
	(3.0)	(3.8)	(2.3)	(3.4)
25–50	2.8	3.8	5.9***	−7.6**
	(2.7)	(3.7)	(1.9)	(3.8)
0–25	1.4	7.9**	1.7	1.4
	(2.5)	(3.6)	(2.3)	(3.5)
Mean, all participants	16.6	23.9	8.1	11.9
Observations	2,705	2,705	2,705	2,705
R^2	0.22	0.10	0.12	0.08

Notes: This table reports OLS estimates of the specification of Table 5, without the "not found" indicator, for the 2,705 participants (46%) whose undergraduate institution we found. Robust (HC1) standard errors in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.10: Robustness to LinkedIn Matching (Top-10 Coefficient)

		LinkedIn matches kept		Drop 10% most
	Baseline	Top 25%	All	common names
	(1)	(2)	(3)	(4)
A. Career outcomes				
Top 10 PhD	34.2***	37.8***	33.3***	36.1***
	(3.4)	(3.6)	(3.4)	(3.6)
Major prize	16.6***	18.2***	16.3***	17.1***
	(3.4)	(3.6)	(3.2)	(3.5)
Leading tech firm	9.9***	7.6***	11.6***	9.6***
	(2.5)	(2.4)	(2.5)	(2.6)
Founder/CEO	4.9*	3.5	5.1*	6.3**
	(2.8)	(2.8)	(2.8)	(3.0)
B. Field of work				
Academia	−6.7*	−6.6*	−6.2*	−7.6**
	(3.6)	(3.7)	(3.5)	(3.7)
Math	−6.5*	−7.1*	−6.4*	−6.7*
	(3.5)	(3.7)	(3.4)	(3.7)
Finance	10.3***	11.2***	10.2***	11.4***
	(2.7)	(2.9)	(2.7)	(2.9)
Observations	5,928	5,928	5,928	5,330
Matched to a LinkedIn profile	32.1%	17.7%	40.2%	31.3%

Notes: This table reports the OLS coefficient on a top-10 undergraduate institution from the specification of Table 3, in percentage points. Column 1 is the baseline sample. Columns 2 and 3 keep LinkedIn matches whose probability-forest score is in the top 25% or 100% of scores (baseline: 70%). Column 4 excludes participants whose standardized name appears more than 41 times in LinkedIn data (the 90th percentile across all participants). Matched to a LinkedIn profile: share of participants in the estimation sample matched to a profile. Robust (HC1) standard errors in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

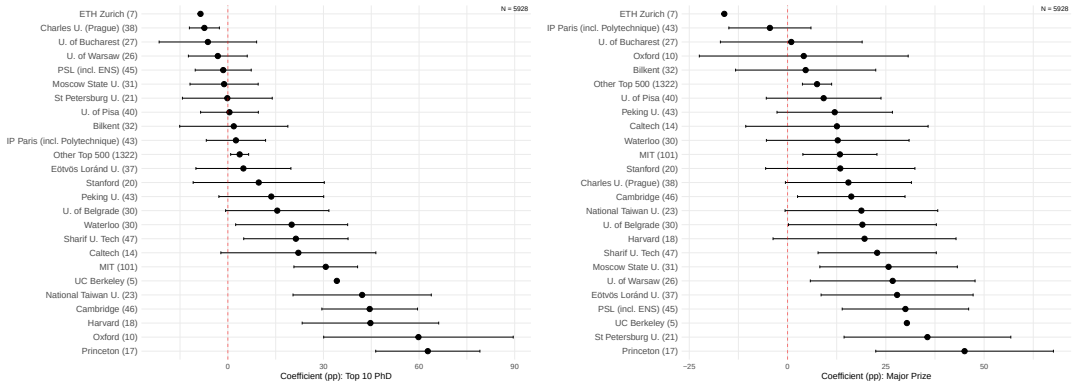
Table A.11: Robustness to LinkedIn Matching: Sensitivity to Unobserved Confounding

	Baseline		LinkedIn: top 25%		LinkedIn: all		Drop common names	
	$RV_{q=1}$	k_0	$RV_{q=1}$	k_0	$RV_{q=1}$	k_0	$RV_{q=1}$	k_0
A. Career outcomes								
Top 10 PhD	19.6%	63.3	21.0%	66.2	19.4%	60.4	20.9%	69.7
Major prize	8.5%	28.5	8.9%	27.9	8.5%	28.5	8.8%	29.8
Leading tech firm	8.0%	125.3	7.1%	108.4	9.1%	98.8	7.9%	119.1
Founder/CEO	3.2%	26.8	2.3%	21.1	3.2%	28.3	4.0%	33.6
B. Field of work								
Academia	2.6%	8.1	2.5%	7.3	2.5%	6.5	3.0%	8.2
Math	2.7%	7.0	2.8%	6.5	2.7%	6.6	2.8%	6.9
Finance	7.3%	62.0	7.8%	67.0	7.3%	52.7	8.0%	53.5

Notes: This table reports sensitivity statistics (Cinelli and Hazlett, 2020) for the top-10 coefficients of Table A.10, with the specification and benchmark of Table 4; column 1 reproduces that table. $RV_{q=1}$: minimum partial R^2 of a confounder with both treatment and outcome needed to reduce the estimate to zero. k_0: how many times as strongly as IMO performance a confounder would need to be associated with treatment and outcome to reduce the estimate to zero.

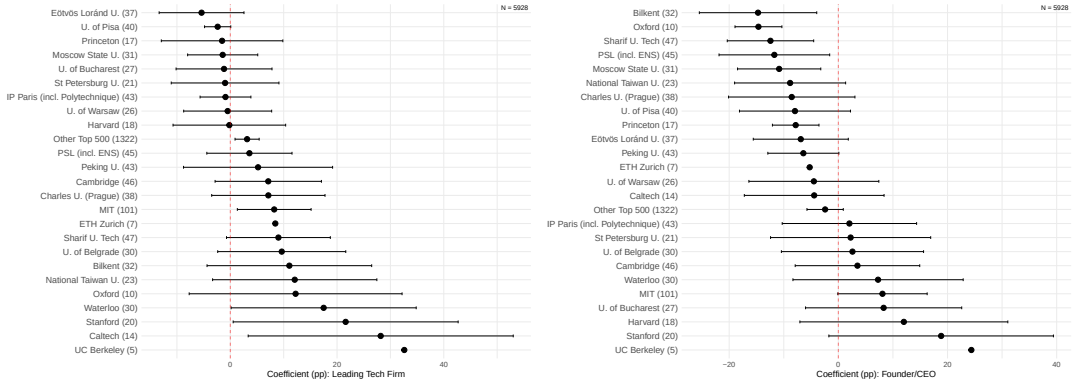
C University-Level Coefficient Plots

Figure A.6: University-Specific Coefficients: Academic Outcomes (Non-US/UK Participants)



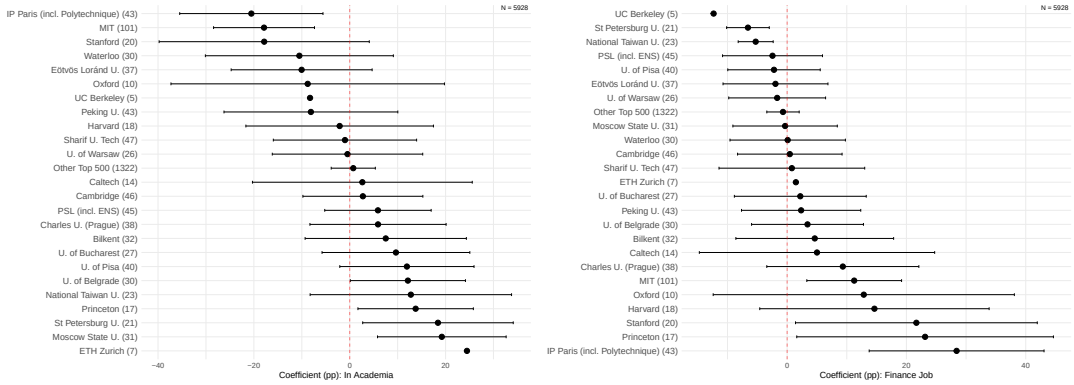
Notes: Coefficients (outcomes $\times 100$) on indicators for universities attended by at least 20 medalists with last competition ≤ 2005 or ranked in the combined QS top 10, and for any other top-500 university ("Other Top 500"); omitted category: a university outside the top 500. Controls as in Table 3: a quadratic in the IMO score percentile, a female indicator, a "UG not found" indicator, and fixed effects for country, last-competition year, and number of participations (capped at four). Sample: non-US/UK participants with last competition ≤ 2005 ($N = 5{,}928$). 95% CIs (HC1); attendee counts in parentheses; CIs omitted below 10 attendees; universities with fewer than 5 attendees not shown.

Figure A.7: University-Specific Coefficients: Tech and Entrepreneurship Outcomes (Non-US/UK Participants)



Notes: Coefficients (outcomes $\times 100$) on indicators for universities attended by at least 20 medalists with last competition ≤ 2005 or ranked in the combined QS top 10, and for any other top-500 university ("Other Top 500"); omitted category: a university outside the top 500. Controls as in Table 3: a quadratic in the IMO score percentile, a female indicator, a "UG not found" indicator, and fixed effects for country, last-competition year, and number of participations (capped at four). Sample: non-US/UK participants with last competition ≤ 2005 ($N = 5{,}928$). 95% CIs (HC1); attendee counts in parentheses; CIs omitted below 10 attendees; universities with fewer than 5 attendees not shown.

Figure A.8: University-Specific Coefficients: Academia and Finance (Non-US/UK Participants)



Notes: Coefficients (outcomes $\times 100$) on indicators for universities attended by at least 20 medalists with last competition ≤ 2005 or ranked in the combined QS top 10, and for any other top-500 university ("Other Top 500"); omitted category: a university outside the top 500. Controls as in Table 3: a quadratic in the IMO score percentile, a female indicator, a "UG not found" indicator, and fixed effects for country, last-competition year, and number of participations (capped at four). Sample: non-US/UK participants with last competition ≤ 2005 ($N = 5{,}928$). 95% CIs (HC1); attendee counts in parentheses; CIs omitted below 10 attendees; universities with fewer than 5 attendees not shown.

D Validation of University Coding

We validated our university coding against two external administrative sources. In both cases, we compare the source to our combined coding (manual + LLM + LinkedIn) before it incorporated any information from either source. For MIT, we use all 2015–2020 medalists, whom the Registrar checked; for Cambridge, we use 2015–2019 medalists, since most 2020 medalists had not graduated by the last yearbook available.

MIT enrollment verification. In December 2024, MIT's Registrar's Office verified the full list of 2015–2020 medalists against its enrollment records. The Registrar matched names exactly or on the first three letters of each name, and checked that each matched student started at MIT within two years of the medalist's last IMO participation. Among 2015–2020 medalists, our combined coding finds 114 MIT undergraduates; the Registrar's records reveal 8 more. This yields an inflation ratio of $1.07 = (114 + 8)/114$. We incorporated the Registrar's records into our final coding.

Cambridge graduation yearbooks. We obtained Cambridge University's commencement books from 2018 onward, which list students' first initial and surname alongside college-wide photographs. The partial name information and inability to distinguish graduate from undergraduate students create a high false-match rate. Our combined coding finds 85 Cambridge medalists among 2015–2019 participants. We matched all medalists against the yearbooks, counting a match when the yearbook year falls three to six years after the medalist's last IMO participation. Among medalists our manual coding places at another university, 5.4% produced a false match. False matches are more frequent for common surnames and for names without a second initial, so we predict each medalist's false-match probability from these two characteristics, estimated on the medalists placed at other universities. Among medalists not coded at Cambridge, yearbook matches exceed the predicted false matches. Only 63% of the medalists we code at Cambridge appear in the yearbooks, so we divide this excess by that share to obtain the number of Cambridge medalists we missed. Depending on whether we count matches up

to four, five, or six years after the IMO, this number ranges from 12 to 15; we use the median, 12. We consider this estimate conservative: matches five to six years after the IMO, when few medalists complete an undergraduate degree, also exceed the predicted false matches, which suggests that graduate students inflate the excess. Adding 2 medalists we later verified individually, our combined coding misses about 14 Cambridge medalists. This yields an inflation ratio of $1.17 = (85+14)/85$.

The pooled inflation ratio across both institutions is $1.11 = (114+8+85+14)/(114+85)$. We extrapolate this ratio to other top-10 universities when estimating the full allocation of medalists to university tiers. At MIT, our final coding already includes the Registrar's records; at Cambridge, we add the 16 medalists the yearbooks suggest we still miss among 2015–2020 medalists.

E A Model of Applications, Admission, and Enrollment

Enrollment-only choice models treat every university in a student's choice set as available: a student who does not enroll abroad is read as not wanting to. This appendix models the applications that precede enrollment. Under the restrictions in Section E.3, the model separates the taste for staying home from the costs of applying and the probability of admission. Students face two (perceived) application costs: a one-time cost of entering the American or British application system (tests, credential formats, essay and personal-statement conventions), the system-entry cost, and a cost for each application, the per-application cost. Both are paid before enrollment tastes realize, and admission is uncertain in between. Unlike enrollment-only models, the model can simulate removing the system-entry costs and guaranteeing admission; it also simulates scholarships that lower the price of attending. The application stage builds on the simultaneous-search problem of Chade and Smith (2006), with the per-application decision rule described below; inferring an unobserved application stage from final choices relates to the consideration-set problem of Abaluck and Adams-Prassl (2021).

Timing. First, the student decides which application systems to enter, paying the system-entry costs; universities outside the US and UK take applications one by one and require no system entry. Second, she chooses where to apply, paying a per-application cost. At that point she knows (or has beliefs about) each option's rank, price, language of instruction, location, and admission probability, but not her idiosyncratic tastes, which she learns only at enrollment. Third, each application is accepted or rejected. Fourth, she learns her tastes and enrolls at her favorite among the options she holds: her home universities, which require no application, plus the foreign universities that admitted her. We observe only the final enrollment.

E.1 Sample, choice set, and prices

Medalists from the 2012–2020 cohorts with an observed university ($N = 1{,}428$) choose among 145 alternatives. North Korea's 24 medalists are excluded. The alternatives are the most common destination universities together with every US and UK university attended by any medalist in the sample, plus four composites whose attributes are measured from the destinations they stand in for: the other-home composite (priced at the origin's domestic cost for a medalist), the other-US composite (priced at the US system's cost-of-attendance rule), the other-UK composite (priced at the audited fees of a median non-Oxbridge UK university), and the other-foreign composite, which collects the remaining destinations outside the US and UK (median rank 150) and is priced at the international average for ranks 51–500. Universities without a rank are assigned rank 800.

For each university we compiled pricing *rules* rather than single prices: domestic, fee-bloc (EU/EEA home fees, post-Soviet budget places), and international tuition; living costs; need-based aid policies, with full-need institutions represented through their aid formulas (need-blind and need-aware alike, since need-aware universities met the full need of the internationals they admitted); means-tested bursaries open to EU students at UK universities; automatic olympiad and merit scholarships; stipends paid to students; and origin-country government scholarships

for study abroad. The price p_{ij} is the rule evaluated at student i's nationality, fee-bloc membership, cohort, and family income (proxied by twice origin GDP per capita), in thousands of 2018 US dollars per year including room and board. The rules were audited against archived fee schedules, aid policies, and scholarship regulations (reports in the replication package).

E.2 Model

Enrollment utility. Let z_i denote standardized log GDP per capita of student i's origin country. Student i's utility from enrolling at university j is

$$u_{ij} = q_r Q_j + q_{r2} Q_j^2 + \theta_L \,\mathrm{Lang}_{ij} + \gamma_i \mathrm{Home}_{ij} + \gamma_c \mathrm{Cont}_{ij} + \omega_{OF} \mathrm{OF}_j - \beta_i p_{ij} + \varepsilon_{ij},$$

where $Q_j = \log 1000 - \log r_j$ is a rank index that rises as the university's global rank r_j improves: the logarithm makes a given rank gap matter more near the top (rank 1 versus 10) than further down (rank 401 versus 410), and subtracting from $\log 1000$ makes the index zero at rank 1000. Lang_{ij} equals one when j teaches in a language of schooling of i's origin; Home_{ij} and Cont_{ij} indicate universities in i's country and on i's continent. Home taste and price sensitivity vary with origin income: $\gamma_i = \gamma_0 + \gamma_y z_i$ and $\beta_i = \beta_0 e^{-b_y z_i}$. OF_j marks the other-foreign composite. The composite pools about thirty institutions; because a student who chooses it can pick the best of them, its averaged attributes understate its value, and the intercept ω_{OF} captures the difference. The enrollment taste shock ε_{ij} is type-I extreme value, independent across options, and realized only at enrollment; its scale defines the utility unit, which we call a util. Apart from ω_{OF}, a university's appeal depends only on its rank, language, location, and price, and tastes do not vary with IMO performance.

Admission. An application to foreign university j succeeds with probability

$$\pi_{ij} = \Lambda\left(\kappa_0 - \kappa_r Q_j + a_j + \rho_A \mathrm{OlyAdmit}_{ij} + \rho_S \mathrm{OlySchol}_{ij} + \kappa_s \mathrm{Perf}_i + \kappa_f \mathrm{Fem}_i D_j\right), \qquad (5)$$

where Λ is the logistic distribution function. The level κ_0 and rank slope κ_r describe how admission probabilities vary across universities; $\kappa_r > 0$ means that higher-ranked universities admit with lower probability. Perf_i is the student's best IMO score percentile, standardized to mean zero and standard deviation one. κ_f shifts women's admission probability only at the $D_j = 1$ universities whose admission has a discretionary component (essays, interviews, holistic file review: the American destinations, Oxford, Cambridge, Imperial, and a few private universities elsewhere), not at universities that admit through anonymous examinations or points formulas. a_j is a university-specific admission intercept (receptivity) to medalists, estimated for the two named destinations with the largest medalist intake, MIT and Cambridge, and for the other-foreign composite; $a_j = 0$ elsewhere.

$\text{OlyAdmit}_{ij} = 1$ if university j had a documented admission policy for international olympiad medalists during most of 2012–2020—admission without the entrance examination, the maximum admission score, or a dedicated olympiad track—that covered student i's nationality. This applies to the National University of Singapore, Nanyang Technological University, Bilkent, ELTE, Jagiellonian, Warsaw, Zagreb, Belgrade, Tartu, and Alexandru Ioan Cuza for all foreign medalists, to Charles University for Slovak medalists, and to Belarusian State University for medalists from Russia, Kazakhstan, Kyrgyzstan, and Tajikistan. $\text{OlySchol}_{ij} = 1$ if j awarded an automatic scholarship to olympiad medalists of i's nationality: Waterloo, HKUST, KAIST, and Bilkent for all foreign medalists, the National University of Singapore for Asian medalists, and HSE, St Petersburg, MIPT, and Belarusian State for medalists from the Eurasian Economic Union. Universities that pay for medalists to attend also recruit them; the scholarship's value additionally lowers the price p_{ij} in enrollment utility. Both indicators were coded from university regulations and admissions pages (sources in the replication package).

Application costs. The system-entry costs vary with access to the admissions tests each system requires, measured by the standardized per-capita scarcity of test centers in the student's

origin country (higher is worse access):

$$F_{US,i} = \alpha_{US} + g_{sat}\text{SAT}_i + g_{toefl}\text{TOEFL}_i, \qquad F_{UK,i} = \alpha_{UK} + g_{step}\text{STEP}_i + g_{toefl}\text{TOEFL}_i. \quad (6)$$

American universities require the SAT, British universities the UK mathematics admissions tests, and both require English-language tests. These scarcities enter only the system-entry costs, not utility or admission. No student can be subsidized to enter a system: $F_{US,i} \geq 0$ and $F_{UK,i} \geq 0$. The per-application cost is

$$c_{ij} = \begin{cases} c_{US} & j \text{ American}, \\ 0 & j \text{ British (UCAS: up to five choices on one form and fee)}, \\ c_{OTH} & j \text{ outside the US and UK}. \end{cases} \quad (7)$$

Enrollment, given the options held. We assume that a student holds her home universities without applying, because many national systems admit olympiad medalists without an entrance examination (olympiad recruitment, post-Soviet budget places, automatic olympiad scholarships); the application costs and admission probabilities are therefore those of applying abroad. Write $u_{ij} = v_{ij} + \varepsilon_{ij}$ and $e_{ij} = \exp(v_{ij})$. A student who holds her home options $\mathscr{H}_i$ plus a set A of admitted foreign options enrolls at j with probability

$$\Pr(\text{enroll at } j \mid A) = \frac{e_{ij}}{H_i + \sum_{k \in A} e_{ik}}, \qquad H_i \equiv \sum_{k \in \mathscr{H}_i} e_{ik}. \quad (8)$$

The value of a portfolio. At the application stage the taste shocks have not realized, so a portfolio $\mathscr{P}$ of applications is valued by the expected utility of the enrollment stage it leads to. With independent admissions,

$$W_i(\mathscr{P}) = \mathbb{E}_{A \subseteq \mathscr{P}}\left[\log\left(H_i + \sum_{j \in A} e_{ij}\right)\right] - \sum_{j \in \mathscr{P}} c_{ij}, \quad (9)$$

where the expectation is over which applications succeed, each with probability π_{ij}.

Application decisions. The marginal value of applying to j is its leave-one-out increment. Adding j changes the value only when j admits her, and then by the log-sum gain of adding e_{ij} to what she already holds:

$$\Delta_{ij} = \pi_{ij}\,\mathbb{E}_{A_{-j}}\left[\log\left(H_i + e_{ij} + \textstyle\sum_{k\in A_{-j}} e_{ik}\right) - \log\left(H_i + \textstyle\sum_{k\in A_{-j}} e_{ik}\right)\right], \tag{10}$$

where A_{-j} is the admitted subset of her other applications. The increment vanishes as $\pi_{ij} \to 0$ and shrinks as the rest of the portfolio grows. Each application decision includes an option-specific shock η_{ij}, logistic with scale τ_a, that captures circumstances of the decision unrelated to enrollment utility (a teacher's advice, a deadline). The student applies to j when $\Delta_{ij} - c_{ij} + \eta_{ij} > 0$, which happens with probability

$$\lambda_{ij} = \Lambda\left(\frac{\Delta_{ij} - c_{ij}}{\tau_a}\right). \tag{11}$$

She decides on each application separately and, when she weighs option j, treats her other applications as uncertain: the expectation in (10) is over the other options' availability, each available with probability $\mu_{ik} = \lambda_{ik}\pi_{ik}$. Equations (10) and (11) thus define a fixed point $\lambda_i = \Lambda\big((\Delta_i(\lambda_i) - c_i)/\tau_a\big)$ in the application probabilities (Section E.8). Holding a university's appeal fixed, a higher admission probability raises Δ_{ij} and hence the probability of applying.

System entry. The student pays $F_{US,i}$ once to apply to American universities and $F_{UK,i}$ once for British ones. Entry is a joint choice over the four subsets $\mathscr{S} \subseteq \{US, UK\}$ of systems, because the systems' options substitute for one another. Let $G_{i\mathscr{S}}$ be the value of the application stage when exactly the systems in $\mathscr{S}$ are open: the expected log-sum term of (9) over applications and admissions, with each open option available with probability μ_{ik}, minus the expected per-application costs $\sum_k \lambda_{ik} c_{ik}$; and let $F_{i\mathscr{S}} = \sum_{g\in\mathscr{S}} F_{g,i}$. The entry decision includes its own

shock, type-I extreme value with scale τ_e, which captures circumstances that affect a whole system at once: a school counselor who knows the American process, a classmate applying to Britain, a family's view of studying in a given country. She enters subset $\mathscr{S}$ with probability

$$\psi_{i\mathscr{S}} = \frac{\exp\left((G_{i\mathscr{S}} - F_{i\mathscr{S}})/\tau_e\right)}{\sum_{\mathscr{S}'} \exp\left((G_{i\mathscr{S}'} - F_{i\mathscr{S}'})/\tau_e\right)}. \tag{12}$$

Section E.3 explains which patterns distinguish τ_e from τ_a.

The probability of an observed enrollment. A foreign option is available if its system was entered, an application filed, and admission granted. System entry is common to all options of a system—a student who did not enter the American system holds no American option—so the likelihood mixes over the four entry subsets with the weights (12). Given the subset, option k is available with probability $\mu_{ik}(\mathscr{S}) = \lambda_{ik}\pi_{ik}$ if its system is open (always, for universities outside the US and UK) and zero otherwise, independently across options. The probability that student i enrolls at foreign option j is

$$P_i(j) = \sum_{\mathscr{S}} \psi_{i\mathscr{S}}\, \mu_{ij}(\mathscr{S})\, \mathbb{E}_{A_{-j}|\mathscr{S}} \left[\frac{e_{ij}}{H_i + e_{ij} + \sum_{k \in A_{-j}} e_{ik}} \right], \tag{13}$$

and at a home option $j \in \mathscr{H}_i$

$$P_i(j) = \sum_{\mathscr{S}} \psi_{i\mathscr{S}}\, \mathbb{E}_{A|\mathscr{S}} \left[\frac{e_{ij}}{H_i + \sum_{k \in A} e_{ik}} \right], \tag{14}$$

where A (A_{-j}) is the random set of available foreign options (other than j).

E.3 Identification

We observe neither applications nor admission decisions; the likelihood uses final enrollments only. Table A.12 lists, for each group of parameters, the variation that identifies it and whether identification rests on revealed preference, an exclusion restriction, functional form, or an as-

sumption.

Table A.12: Sources of identification

Parameters	Role	Identifying variation	Type
q_r, q_{r2}, θ_L, γ_0, γ_y, γ_c, β_0, b_y, ω_{OF}	enrollment tastes	enrollment shares across students who face different prices, languages, and home options	revealed preference
κ_s, κ_f	admission	performance and gender gradients in foreign enrollment	exclusion restriction
κ_0, κ_r	admission level and rank slope	how the performance gradient varies across universities	functional form (logistic)
ρ_A, ρ_S	olympiad policies	which universities have policies and which nationalities they cover	policy variation within universities
a_{MIT}, a_{Cam}	receptivities	enrollment at MIT and Cambridge relative to their rank	university intercepts
g_{sat}, g_{step}, g_{toefl}	system-entry cost slopes	test-center scarcity across origin countries	exclusion restriction
α_{US}, α_{UK}, c_{US}, c_{OTH}	application costs	substitution between systems and between options	functional form and portfolio structure
τ_a, τ_e	shock scales	substitution within a system versus across systems	functional form

Admission. Two restrictions identify the admission parameters. First, IMO performance and gender enter admission and nothing else, so any performance gradient in who reaches which universities, conditional on covariates, is attributed to admission. Second, the logistic is flat at both ends, so the steepness of the performance gradient in enrollment at a university tells how far its admission probability is from one-half, and the level of enrollment tells on which side: a university that admitted few medalists could not enroll many of them. Together, these restrictions identify the level κ_0 and slope κ_r of the admission curve. Because the second restriction relies on the logistic form, and because admission enters availability multiplied by the application probability, the admission level is identified by functional form and estimated with less precision than the tastes. The olympiad-policy coefficients ρ_A and ρ_S are identified by which universities have such policies and, within a university, by which nationalities they cover.

Application costs and shocks. The system-entry cost slopes g_{sat}, g_{step}, and g_{toefl} are identified because test-center access is excluded from utility and admission. The two shock scales are measured against the enrollment taste scale. An entry shock opens or closes every option of a system at once, whereas application shocks act option by option. Although availability is not observed, the two shocks imply different substitution patterns in enrollment: when a system is closed, students substitute away from all of its universities together.

Restrictions. We take no parameter from outside sources. The no-subsidy restrictions $F_{US,i} \geq 0$ and $F_{UK,i} \geq 0$ are imposed in estimation. At the estimate, the American restriction binds for the students with the best test access, so α_{US} equals the level at which their entry cost is zero and is reported without a standard error; the British restriction does not bind. The estimated admission probability of the other-foreign composite approaches one, since a student who applies to the institutions it pools is admitted to at least one of them; we fix a_{OF} so that admission is certain.

E.4 Estimation and inference

We maximize the likelihood (13)–(14). Every expectation in it is computed exactly, through the Laplace transform of the random total weight of the available options, up to a one-dimensional quadrature whose error is negligible (Section E.8). We use L-BFGS followed by Newton steps, with the Hessian computed by central differences of the exact gradient and recomputed at least every eight steps. We start the optimizer from three points, two of them random perturbations of the parameter vector. All three reach the same maximum, where the largest absolute gradient is 1.4×10^{-5} and the Hessian is positive definite (smallest eigenvalue 1.1). We report standard errors from the inverse Hessian and a 95% percentile band from 200 bootstrap samples of the 1,428 students drawn with replacement, re-estimating the model in each from the full-sample estimate; 189 of the 200 bootstrap estimates converge (largest absolute gradient below 10^{-3}), and the bands use these.

E.5 Estimates

Tastes. Utility rises with rank at an increasing rate toward the top: the quadratic coefficient is 0.13 (bootstrap 95% band 0.08–0.18), and the linear coefficient is small and imprecise. The taste for home universities is 2.4 utils for a student from a country of average income and rises with income; the language bonus is 2.2 utils, and a university on the student's continent is worth 1.3 utils. A $50,000 annual price difference is worth about 0.8 utils at average origin income, and price sensitivity falls with income ($\hat{b}_y = 0.32$, bootstrap 95% band 0.04–0.61).

Admission. Admission probabilities fall with rank ($\hat{\kappa}_r = 0.17$, bootstrap 95% band 0.04–0.99). A foreign university admits a male medalist of average IMO performance with probability 14% at Harvard and 16% at ETH Zurich, against 25% at IIT Bombay; MIT admits him with probability 33% and Cambridge with 74%. Automatic olympiad scholarships raise the odds of admission by a factor of 2.7: the admission probability is 42% at Waterloo, against 21% without the scholarship. Documented olympiad admission policies raise the odds by a factor of 1.7 ($\hat{\rho}_A = 0.55$, bootstrap 95% band 0.07–0.92). Together the two give the National University of Singapore an admission probability of 50% for an Asian medalist, against 28% for a medalist from elsewhere, who is covered by its admission policy but not by its scholarship. Admission rises with IMO performance: one standard deviation raises the odds by a factor of 1.9. Women's odds at discretionary-admission universities are higher by a factor of 2.8. The level of the admission curve is imprecise: in a minority of bootstrap samples it moves toward certain admission, which widens the upper ends of the bands for κ_0, κ_r, and ρ_S (Table A.13).

Application costs and shocks. Among students for whom each system is foreign, the median system-entry cost is 1.6 utils for the American system and 2.9 utils for the British one (bootstrap 95% bands 0.8–2.7 and 0.9–4.3). Each American application costs 0.06 utils and each application outside the US and UK 0.8 utils (bootstrap 95% bands 0.00–0.13 and 0.07–1.86). Worse access to English-language testing raises the system-entry costs (bootstrap 95% band of g_{toefl}: 0.40–1.37); the SAT and UK-test slopes are imprecise. The application shocks

have a scale of 0.25 relative to the enrollment taste shock (bootstrap 95% band 0.03–0.49): once a system is open, application decisions respond about four times as strongly to differences in expected value as enrollment decisions respond to differences in utility. The entry shocks have a scale of 1.25. At the estimates, 32% of the students for whom the American system is foreign enter it, 22% enter the British one, and 5% enter both; a student files 11.6 applications abroad on average, a number implied by the model rather than observed.

E.6 Fit

The model matches the aggregate allocation: predicted top-10, US, and UK enrollment shares of 31.7%, 23.0%, and 13.1%, against 32.4%, 22.8%, and 13.6% observed. It understates the performance gradient: among medalists in the top quartile of IMO performance it predicts 35.8% at top-10 universities, against 43.9% observed.

E.7 Counterfactuals

Each counterfactual re-solves the full model—system entry, applications, admission, and enrollment—for the prediction sample (the 1,428 estimation students plus the 215 medalists whose university we could not find), changing one primitive and nothing else. In particular, university capacities and admission rules other than the one changed are held fixed. Guaranteeing admission at the top-10 universities moves the predicted top-10 share most, from 31.0% to 77.6% (bootstrap 95% band 64.1–93.7; Table A.14). Removing the US and UK system-entry costs raises it to 53.4% (44.8–63.8). Making tuition and living costs free raises it to 35.8% when the subsidy is limited to the top-10 universities, 34.3% at the BIG partner universities, and 34.7% when it applies everywhere. The changes are similar for developing-country medalists, whose predicted top-10 share is 26.7% at baseline.

Table A.13: Estimates of the application model, 2012–2020 medalists

Parameter	Estimate	s.e.	Bootstrap 95% band
Enrollment tastes (utils)			
Quality, rank (q_r)	0.15	(0.09)	[−0.07, 0.34]
Quality, rank^2 (q_{r2})	0.13	(0.02)	[0.08, 0.18]
Language match (θ_L)	2.24	(0.21)	[1.67, 2.70]
Home (γ_0)	2.43	(0.42)	[1.55, 3.36]
Home × income (γ_y)	0.38	(0.10)	[0.20, 0.59]
Continent (γ_c)	1.28	(0.17)	[0.79, 1.62]
Price (β_0), utils per \$1,000/yr	0.0151	(0.0037)	[0.0079, 0.0215]
Price × income (b_y)	0.32	(0.15)	[0.04, 0.61]
Other-foreign composite, intercept (ω_{OF})	2.76	(0.51)	[0.86, 4.31]
Admission (log-odds)			
Level (κ_0)	−0.77	(0.49)	[−2.12, 4.23]
Rank slope (κ_r)	0.17	(0.07)	[0.04, 0.99]
Performance (κ_s)	0.64	(0.11)	[0.43, 1.00]
Female, discretionary schools (κ_f)	1.01	(0.25)	[0.45, 1.56]
MIT receptivity (a_{MIT})	1.21	(0.16)	[0.98, 1.89]
Cambridge receptivity (a_{Cam})	2.72	(0.32)	[2.20, 4.24]
Other-foreign composite (a_{OF})	$+\infty$	at boundary	
Olympiad admission policy (ρ_A)	0.55	(0.19)	[0.07, 0.92]
Olympiad scholarship (ρ_S)	0.98	(0.29)	[0.41, 16.74]
Application costs (utils) and shocks			
UK entry cost (α_{UK})	3.12	(0.74)	[0.98, 4.78]
US entry cost (α_{US})	1.70	at boundary	[0.80, 2.75]
US per-application cost (c_{US})	0.06	(0.04)	[0.00, 0.13]
Other-system per-application cost (c_{OTH})	0.82	(0.35)	[0.07, 1.86]
SAT-access slope (g_{sat})	0.01	(0.17)	[−0.31, 0.36]
UK-test-access slope (g_{step})	0.31	(0.19)	[−0.01, 0.74]
English-test slope (g_{toefl})	0.91	(0.22)	[0.40, 1.37]
Application-shock scale (τ_a)	0.246	(0.093)	[0.028, 0.490]
Entry-shock scale (τ_e)	1.251	(0.243)	[0.449, 1.794]
Implied quantities (at the estimate)			
System entry rate (%), students for whom the system is foreign:			
US	31.9		[26.1, 47.4]
UK	21.7		[16.8, 34.3]
Both (foreign to both)	5.3		[2.3, 15.7]
Applications abroad per student	11.55		[7.95, 23.42]
N		1,428	
Log-likelihood		−3435.0	
Bootstrap replications		189	

Notes: This table reports maximum-likelihood estimates for the 2012–2020 medalist cohorts with an observed university, in utils (units of the enrollment taste shock); implied quantities are evaluated at the estimates. α_{US} and a_{OF} are at boundaries and have no standard error ($F_{US,i} \geq 0$ binds for the student with the best test access; admission to the other-foreign composite is certain); the band for α_{US} reflects how that floor varies across bootstrap samples. Standard errors from the inverse Hessian in parentheses; bootstrap bands are the 2.5th and 97.5th percentiles across 189 converged replications.

Table A.14: Counterfactual allocations

	Enrollment share (%)				Entry rate (%)		
Regime	Top-10	US	UK	Home	US	UK	Applications
A. All medalists							
Baseline (model prediction)	31.0 [28.9, 33.2]	22.4	12.8	56.7	31.7	21.4	11.51
Free tuition and living:							
everywhere	34.7 [32.1, 37.9]	23.0	16.7	51.8	31.8	25.3	11.80
at top-10 universities	35.8 [32.8, 39.3]	22.4	17.0	53.6	31.5	25.7	11.73
at BIG partner universities	34.3 [31.8, 37.5]	21.1	17.2	54.5	30.3	25.9	11.46
Zero US and UK entry costs	53.4 [44.8, 63.8]	31.4	29.1	37.8	52.1	65.5	18.21
Guaranteed admission at top-10 universities	77.6 [64.1, 93.7]	53.8	10.1	23.1	55.5	17.6	16.01
B. Developing-country medalists (World Bank low and middle income): top-10 share							
Baseline (model prediction)	26.7 [24.5, 29.1]						
Free tuition and living:							
everywhere	31.9 [28.0, 35.5]						
at top-10 universities	33.0 [29.0, 36.9]						
at BIG partner universities	31.1 [27.5, 34.8]						
Zero US and UK entry costs	54.7 [46.8, 65.3]						
Guaranteed admission at top-10 universities	79.0 [65.5, 95.0]						

Notes: This table reports predicted enrollment shares, system-entry rates, and applications abroad per medalist under the estimated model (baseline) and under counterfactuals that each change one primitive, for the prediction sample (2012–2020 cohorts, including the medalists whose university we could not find), at the estimates of Table A.13. Free tuition and living: the price term is removed from utility at the named universities (BIG partners: Cambridge, Oxford, Imperial, PSL, Institut Polytechnique de Paris). Zero entry costs: α_{US}, α_{UK}, and the test-access slopes are set to zero; the entry shocks are kept. Guaranteed admission: $\pi_{ij} = 1$ at the top-10 universities; applications are still chosen. Entry rates: share entering the US (UK) system among medalists for whom it is foreign. Bootstrap 95% percentile bands across 189 replications in brackets.

E.8 Computation

Exact expectations. Every expectation in (9)–(14) is over the random total weight $Y = \sum_k B_k e_k$ of the available options, where the B_k are independent Bernoulli variables with probabilities μ_k. With about 144 foreign options per student, direct enumeration of the 2^{144} availability patterns is impossible. We compute the expectations exactly through the Laplace transform of Y. Because the B_k are independent, the transform factorizes:

$$M(t) \equiv \mathbb{E}\big[e^{-tY}\big] = \prod_k \big(1 - \mu_k + \mu_k e^{-te_k}\big).$$

Three standard identities, valid for $x > 0$ and $e \geq 0$, express the functions of Y that the model needs as integrals of exponentials: Frullani's integral $\log x = \int_0^\infty (e^{-t} - e^{-xt})\, dt/t$; its difference form $\log(x+e) - \log x = \int_0^\infty e^{-xt}(1 - e^{-et})\, dt/t$; and $1/x = \int_0^\infty e^{-xt}\, dt$. Taking expectations inside the integrals gives

$$\begin{aligned}
\mathbb{E}\big[\log(H_i + Y)\big] &= \int_0^\infty \frac{e^{-t} - e^{-H_i t} M(t)}{t}\, dt, \\
\mathbb{E}\big[\log(H_i + e_j + Y_{-j}) - \log(H_i + Y_{-j})\big] &= \int_0^\infty e^{-H_i t} M_{-j}(t)\, \frac{1 - e^{-e_j t}}{t}\, dt, \\
\mathbb{E}\big[1/(x+Y)\big] &= \int_0^\infty e^{-xt} M(t)\, dt,
\end{aligned}$$

where M_{-j} omits option j's factor. These identities are exact, so the average over 2^{144} availability patterns becomes a one-dimensional integral; the only numerical approximation is the quadrature, whose error we assess below. We evaluate the integrals by the trapezoid rule in $u = \log t$. The integrands are analytic in a strip around the real axis and decay faster than exponentially as $u \to \infty$ and exponentially as $u \to -\infty$; for such integrands the trapezoid rule converges geometrically as the step size shrinks (Trefethen and Weideman, 2014). We use a step of 0.25 over the range where the integrand exceeds 10^{-17} (a few hundred nodes per student). The nodes are fixed multiples of the step, so they do not depend on the parameters and

the likelihood is smooth in them. Leave-one-out products M_{-j} are formed from prefix and suffix products rather than by division, which keeps them exact when an option is available with certainty.

Application fixed point. We solve the fixed point in the application probabilities by 80 damped iterations, $\lambda_i \leftarrow (1-\omega)\lambda_i + \omega\,\Lambda\big((\Delta_i(\lambda_i) - c_i)/\tau_a\big)$, starting from $\lambda_i = 1$, with step $\omega = 0.7\,\tau_a/(\tau_a + 0.07)$. At the estimate, the largest change in the last iteration is below 10^{-10} for every student.

Checks. On a reduced 12-alternative menu, where every availability pattern can be enumerated, the likelihood computed this way equals exhaustive enumeration of the full model—application fixed point, entry mixture, and enrollment—to 10^{-12} at four parameter vectors. At the full menu, the log-likelihood is unchanged to six decimals for quadrature steps from 0.025 to 0.3, and Monte Carlo simulation of the availability patterns (336 student–subset cells, 200,000 draws each) agrees with the computed expectations within sampling error. Gradients are computed in reverse mode through the fixed point and agree with forward-mode automatic differentiation to 10^{-11}.

F LLM Prompt for Automated Data Collection

For each IMO participant, the following prompt was sent to OpenAI's GPT-5 via the Responses API with the web search tool enabled. Placeholders `[NAME]`, `[YEAR]`, and `[COUNTRY]` were filled with the participant's name, last year of IMO participation, and country of representation, respectively.

> `[NAME]` has participated in the International Math Olympiad for the last time in `[YEAR]`, representing `[COUNTRY]`.
>
> You need to collect data on their career trajectory, for an academic study. Start by searching LinkedIn and other personal or institutional pages. Do NOT stop at the first profile you find

or at the first failure; examine multiple sources and cross-check identities before concluding. E.g., ask if the last year of IMO participation makes sense with their current career stage, year of BA, etc. Read resumes when available.

If the person is from a country where English is not commonly spoken, also search in the local language in addition to English.

When determining `BA_institution`, APPLY this pre-Bologna heuristic:

- If the person is European AND the year is < 1999 AND the earliest post-secondary degree found is labeled as a master's/integrated long-cycle (e.g., 'Diplom', 'Magister', 'Laurea' pre-Bologna, 'Licenciatura' pre-Bologna, 'Dipl.-Ing.', or integrated master's such as 'MEng', 'MPhys'), AND that program starts within 0–2 years of the IMO participation (or at typical undergrad entry ages 17–21), THEN TREAT THAT DEGREE'S INSTITUTION AS the `BA_institution` (equivalent to a bachelor under the later three-cycle system).
- If a clear standalone bachelor's exists, prefer it over the heuristic above.
- If evidence is ambiguous, choose the most plausible first-cycle equivalent based on country timelines and degree structure, but still return ONLY the JSON below.

Return the result strictly as a JSON object with the following keys:

- `profile_found`: Write 0 if no reliable information could be found about this person, 1 otherwise.
- `linkedin_profile`: URL to their LinkedIn profile (always look for this).
- `wikipedia_page`: URL to the person's Wikipedia page, if any.
- `personal_page`: URL to the person's personal or academic website, if any.
- `bio`: A concise 10–50 word description of the person's current or past professional activities. For example, "investor, founder, or CEO of company X" or "prominent researcher in analytic philosophy."
- `recognitions`: List major internationally recognized prizes and fellowships given for career achievement. Do not include prizes that are very local, or that have unclear

prestige. Also ignore student/doctoral grants and fellowships, and any IMO medals.

- `academic`: 1 if the person followed an academic research career, 0 otherwise.
- `field`: Their area of work or expertise, such as mathematics, statistics, finance, computer science, business, etc.
- `BA_institution`: The institution where the person got a Bachelor degree (apply the pre-Bologna rule above when applicable).
- `PhD_institution`: The institution where the person got a PhD.

Do not return anything else besides this JSON object. No explanations, apologies, or text outside the JSON.

If any key has no information available, leave its value empty (null or empty string), but do NOT explain or comment on the missing data.

A second call, without web search, classified the career information returned by the first. A short screening prompt first flagged biographies indicating that no public information had been found. For the remaining participants, the model received the `bio` and `field` values and returned binary indicators for mathematics (an academic or research role in mathematics), finance (investment, financial markets, macroeconomics, public finance, banking, asset management, or financial economics, excluding generic business or accounting roles), IT (computer science, software, information technology, and related fields), academia (an academic, research, or teaching position in any domain), founder (founding or co-founding a company), and CEO (chief executive or equivalent top executive role), along with the names of the companies founded or led. The `academic` key of the first prompt is not used.