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

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Abstract

The world's highest-potential students are born everywhere; how many end up at universities below their potential, why, and does it matter for their careers? We answer these questions using 11,424 International Mathematical Olympiad (IMO) participants, linking them to undergraduate institutions and career outcomes. We estimate that only 29% (42%) of recent medalists attend a top-10 (top-50) university. Country of origin is the dominant predictor of attending a top university: the need to migrate imposes a 36–40 percentage point penalty. A regression discontinuity design indicates that informational frictions faced by universities could explain at most one-eighth of the placement gap between developing-country and US/UK medalists. Conditional on IMO performance, top-10 attendance predicts a 32pp increase in top-10 PhD attainment and 5–12pp for academic prizes, leading technology firms, and founding a company. These associations appear robust to omitted variable bias. Ensuring that international students can access leading universities based on merit could thus yield high social returns.

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

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1 Introduction

The highest-potential scientific talent is born everywhere but trained in a handful of places. If the best universities—concentrated in a few wealthy countries—develop this talent more effectively, then high-ability students who attend universities below their potential represent a form of talent misallocation: human capital goes undeveloped (Hsieh et al., 2019). How large is this misallocation, what drives it, and does it matter for careers?

We study these questions using participants in the International Mathematical Olympiad (IMO), an annual competition in which over 100 countries each send up to six pre-university students selected through national olympiads that filter thousands of candidates. IMO participants represent the extreme right tail of the math ability distribution in each country, and their talent extends well beyond test-taking: even bronze medalists go on to win major scientific prizes at rates exceeding those of undergraduates at any top-10 university (Agarwal et al., 2025). Because every participant sits the same exam regardless of nationality, IMO scores provide a globally comparable ability measure—making it possible to ask whether two students of equal demonstrated ability end up at different universities, and with what consequences, depending on where they were born.

Measuring the extent, determinants, and consequences of this misallocation requires linking each participant to both an undergraduate institution and long-run career outcomes. We build a novel dataset covering 11,424 IMO participants from 132 countries over four decades (1981–2020), combining three approaches: manual coding by research teams for 5,784 medalists (undergraduate institution identified for 70%), automated LLM-based web search in local languages for all 11,424 participants, and matching participants to LinkedIn profiles. We validated the combined data against MIT enrollment records and Cambridge graduation yearbooks, confirming that our search found almost all medalists who attended those universities. The resulting dataset identifies an undergraduate institution for 80% of medalists and 55% of all participants—the first source to link a globally comparable population of high-ability students to both their undergraduate institutions and long-run career outcomes.

We begin by asking how well the world's best math talent is allocated across universities. In recent medalist cohorts (2015–2020), we observe that at least 28% attended a top-10 university and at least 61% a top-500 institution, where rank is the better of a university's Shanghai ARWU overall and math subject rankings (Table A.1 lists the universities in each tier). We could not find an undergraduate institution for 15% of medalists in this cohort; imputing these using miss rates calibrated to MIT and Cambridge validation data yields estimates of 29% at a top-10 university, 50% at a top-100, and 70% at a top-500 (Section 3.1, Figure 1). Nearly a third of the

world's best young mathematicians attend universities outside the top 500.

Having established substantial misallocation, we study its predictors. Country of origin is a stronger predictor than ability: IMO performance predicts top-10 attendance (a 20–23pp change across the medalist score range), but the need to migrate imposes a larger penalty (36–40pp). 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. Among developing-country medalists, only 24% attend a top-10 university, compared to near-universal placement for those from the US or UK (Figure 2).

We also test whether informational frictions in how universities select students can explain some of this undermatching. We use a regression discontinuity design to test whether barely receiving or barely missing a medal has a causal effect on top university attendance. We find that the probability of attending a top-10 university rises smoothly with IMO performance, with no jump at the bronze or silver thresholds. Only at the gold threshold is there a significant discontinuity—an 11pp increase, nearly doubling the placement rate—suggesting that the top distinction carries signaling value but that the medal label is otherwise irrelevant for admissions (Section 3.3, Figure 4). Even under the assumption that bronze and silver medalists received the same admissions premium as gold medalists, overall top-10 placement would rise by about 9pp—closing less than one-eighth of the gap between developing-country and US/UK medalists.

The overall evidence suggests that barriers faced by international competitors, rather than preferences for staying home, drive the mismatch. Nearly all US and UK medalists attend top-10 universities—bronze-level talent suffices when migration is not required. The improving allocation trend visible in Figure 5 is driven by MIT and Cambridge, both of which offer need-blind financial aid to international students. Survey data from Agarwal et al. (2023) corroborate: 81% of STEM talent from developing countries report aspiring to study in the US or UK, yet only 29–34% of developing-country medalists actually do so, and 57% cite cost as a very important reason for not applying.

We then ask whether this misallocation matters for careers. We measure four outcomes that capture the channels through which exceptional mathematical talent generates social returns: earning a PhD from a top-10 institution (frontier research training), winning a major academic prize (scientific contribution), working at a leading technology firm (technological innovation), and founding or leading a company (entrepreneurship). Conditional on IMO performance, top-10 attendance is associated with a 32pp increase in top-10 PhD attainment, a 12pp increase in winning a major academic prize, a 7pp increase in working at a leading technology firm, and a 5pp increase in founding a company—large relative to sample averages of 9%, 12%, 4%, and

7%, respectively.

The central concern is selection: students who reach top-10 universities may differ in unobserved ways—wealthier families, stronger ambition—that would produce better careers anywhere. The joint pattern of outcomes is hard to reconcile with that story. Conditional on ability, top-10 attendance predicts *fewer* careers in academia (-9pp) and math (-7pp) and more in finance ($+9$pp); the raw correlation between top-10 attendance and academia is *positive* and flips only after conditioning on ability and country. Wealth predicts, if anything, the wrong sign here: relative to poorer students of the same ability, wealthier students can better afford to pursue low-paying academic careers, yet top-10 attendees shift away from them. Ambition predicts the redirection but not the prizes: if top universities merely attract ambitious students and channel them into finance, thinning the pool that produces academic prizes, prize rates should fall—instead, top-10 attendees win *more* prizes. Fewer academics but more prizes is difficult to explain by who selects in, and is what one expects if top universities raise the productivity of those who stay in research. Formal sensitivity analysis (Cinelli and Hazlett, 2020) quantifies this: an unobserved confounder three times as strongly associated with university attendance and career outcomes as IMO performance itself—the strongest observed predictor of both—would move the top-10 PhD association only from 32 to 28pp, and would overturn none of the career associations.

The associations also vary with ability in a way consistent with complementarity between talent and training. The top-10 PhD premium rises from 21pp for the lowest performance quartile to 33pp for the highest—the mismatch matters most where talent is strongest. Industry outcomes show the reverse pattern: the leading tech firm and founder/CEO associations peak among moderate-ability participants, consistent with comparative advantage sorting the strongest performers toward research and the rest toward industry.

Taken together, our results indicate that a large pool of exceptional talent is trained at institutions below its potential, with measurable differences in career outcomes across science, technology, and entrepreneurship. Because the barrier is primarily financial—roughly $39 million per year would fund the approximately 110 medalists who attend universities outside the top 10 and would consider relocating—it is, in principle, solvable.

We make two contributions relative to prior work. First, we provide the first comprehensive tracking of where the world's top math talent goes to college and what happens afterward. No existing source links a globally comparable population of high-ability students to both their undergraduate institutions and long-run career outcomes across academia, industry, and entrepreneurship. 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 and finds home-country dependence but does not link outcomes to the university attended. Choudhury et al. (2023) study a parallel pattern among top IIT-JEE scorers in India but cover a single country. We cover 132 countries over four decades, combining manual, automated (LLM with online search tools), and probabilistic (matching to LinkedIn) methods validated against administrative records. By measuring outcomes conditional on university tier, ability, and country fixed effects, we estimate the association between university quality and career outcomes across academia, finance, and technology. Our main specification restricts to non-US/UK participants ($N = 5{,}928$), who provide within-country-of-origin variation in university quality.

Second, we connect to and extend several literatures. Hsieh et al. (2019) estimate that barriers facing women and minorities explain 20–40% of US growth since 1960; our data reveal an analogous misallocation at the global level, where country of origin is the binding constraint. We complement the brain drain literature (Docquier and Rapoport, 2012; Beine et al., 2008) by studying not whether talent leaves, but whether it receives training commensurate with its ability. Novosad et al. (2024) document that access to opportunity shapes who becomes a Nobel laureate; Bell et al. (2019) show that childhood exposure to innovation predicts inventive careers for US residents; Chetty et al. (2025) show that non-academic admissions preferences—legacy, athlete, and other non-test-score channels—drive income gaps in Ivy-Plus attendance. Hoxby and Avery (2013) show that most high-achieving, low-income US students never apply to selective colleges despite generous financial aid, and Hoxby and Turner (2015) demonstrate that a low-cost information intervention substantially raises their application rates—the domestic analog of the financial and informational barriers we document at the global level. We study a global population at a later but still formative exposure—undergraduate education—where country of origin plays the role that family income and neighborhood play domestically. A large literature estimates returns to college quality—using regression discontinuity at admission cutoffs (Hoekstra, 2009; Zimmerman, 2019; Anelli, 2020), selection-on-observables matching (Dale and Krueger, 2014), and waitlist-based designs (Chetty et al., 2025)—and finds modest average returns but large returns for disadvantaged students. Our setting is distinctive: we study the extreme right tail of ability, asking whether university quality matters even for those who would plausibly succeed anywhere.

The paper proceeds as follows. Section 2 describes the IMO context and our multi-source data collection. Section 3 documents the allocation of medalists to universities and its predictors. Section 4 estimates the association between university quality and career outcomes, with robustness checks for unobservable selection. Section 5 discusses the financial scale of the problem and concludes.

2 Context and Data

2.1 Context

The International Mathematical Olympiad (IMO) is an annual competition for pre-university students, held since 1959. Each participating country selects a team of up to six students through national olympiads. Contestants sit a two-day exam of six problems. Because problem difficulty may vary across years, we normalize each participant's total score to a within-year percentile. Over our sample period, participation expanded from roughly 30 countries in the early 1980s to over 100 by 2020. Each national team is selected through multi-round olympiads that filter thousands of students down to six, so IMO participants represent the extreme right tail of the within-country math ability distribution. Agarwal et al. (2025) show 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 exceptional talent rather than test-taking skill alone. We focus on the 1981–2020 period, which yields 11,424 unique participants from 132 countries.

2.2 Data

We build our data in four steps: (i) manual biography coding of medalists, (ii) automated LLM-based data collection for all participants, (iii) LinkedIn profile matching, and (iv) linkage to country-level covariates and prize records. Our cleaned data cover 11,424 participants, of whom 5,784 are medalists (1,128 gold, 1,966 silver, 2,690 bronze) and 5,640 are non-medalists.

Participant disambiguation. The official IMO records list each participation as a separate entry by name and country. Because participants can compete in multiple years, we must first consolidate entries belonging to the same individual. We identify participants by a name–country composite key after standardizing names to Latin script, removing accents, and normalizing whitespace. We then apply three rounds of deduplication—exact, substring, and fuzzy string matching—within broad country groups that account for dissolved states (USSR, Yugoslavia, Czechoslovakia), with all fuzzy candidates manually reviewed.[1]

[1] Fuzzy matching uses Jaro-Winkler distance within Double Metaphone phonetic blocks. In total, we consolidated 40 spelling corrections, 23 transliteration variants (e.g., Cyrillic, Greek, Arabic, and Chinese names), and 5 partial-name completions. Only two cases of genuinely distinct individuals sharing the same name and country arose in the full 1981–2020 period; these were disambiguated by participation year.

2.2.1 Manual 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. We searched medalists across three batches (1981–2000, 2001–2014, 2015–2020) and found an undergraduate institution for 70% of them.

2.2.2 Automated Data Collection

To extend coverage beyond medalists and to collect career outcomes, we deployed OpenAI's GPT-5 via the Responses 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 (e.g., mathematics, finance, computer science), undergraduate and doctoral institutions, a list of major international prizes or honors,[2] and binary indicators for career paths (academic, finance, IT, founder, CEO). Local-language search—Mandarin, Russian, Arabic, Vietnamese—matters in development contexts, since many participants' online presence is not in English.

We matched raw institution names from both the LLM and manual coding to OpenAlex (Priem et al., 2022), an open catalog of over 100,000 academic institutions with unique identifiers and country codes. We linked each institution to the Shanghai ARWU overall ranking and the Shanghai math subject ranking, and assigned each university the better (lower) of the two ranks—henceforth "university rank" throughout the paper. This matching step also resolved parent–child ambiguities (e.g., mapping École Polytechnique to Institut Polytechnique de Paris) so that each institution corresponds to the entity that appears in the ranking. 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. Among medalists for whom both sources identified a bachelor's institution, the LLM matched the manual coding 87% of the

[2]Among all participants, 1,154 had at least one career-level recognition reported by the LLM. To make sure we did not miss any important recognitions, we supplemented this procedure with data from Agarwal et al. (2025), which matched olympiad medalists to 127 major international scientific prizes and fellowships. We find that the LLM-based procedure failed to find prizes for only 12 IMO medalists, and we amend our data accordingly.

time. An audit of 50 random discrepancies showed that most arose from participants attending multiple institutions (e.g., a transfer or an integrated degree coded differently). We use LLM-identified institutions only for medalists where the manual coding did not find an undergraduate institution, preserving the manually verified data wherever available. This raises the share of medalists with an identified undergraduate institution from 70% to 78%.

2.2.3 Complementary Data Sources

LinkedIn data. We linked all 11,424 participants to LinkedIn profiles (via Revelio Labs) using a fuzzy name-matching pipeline based on phonetic blocking (Double Metaphone) and Damerau-Levenshtein string distance. A probability forest selected the best candidate for each participant—or classified them as having no LinkedIn presence—using 43 predictors that capture name characteristics, IMO performance, education timing and field alignment, career sector, and cross-source agreement.[3] The forest was trained on medalists for whom research assistants had verified a LinkedIn URL, most collected as a by-product of the manual coding step. We retained the top 70% of match scores (above the 30th percentile) and identified a LinkedIn profile with high confidence for 37% of participants (4,213). From matched profiles, we extracted education histories, career positions, and company information. Appendix Tables A.15–A.18 show that all main results are robust to using 100% or only 25% of the suggested matches. Appendix Tables A.19–A.22 verify that results are unchanged when dropping the 10% of participants with the most frequent names. When multiple sources identified an undergraduate institution, we prioritized manual coding over LLM over LinkedIn. LinkedIn data filled in cases where neither manual coding nor the LLM identified an institution, raising the share with an identified undergraduate institution to 80% for medalists and 55% for all participants.

Country data. We augmented participant records with country-level covariates: World Bank income classification (at the time of first IMO participation), English-speaking population share (from UNESCO data supplemented by manual coding), and bilateral variables from the CEPII Gravity database (geographic distance, colonial ties, common language). We also coded whether each participant's country of origin hosts a top-50 or top-10 Shanghai-ranked university. The World Bank income classification structures the misallocation results: the penalty for attending a lower-ranked institution is concentrated among participants from low-income and lower-middle-income countries, which host none of the world's top-500 universities.

[3]Predictors include exact name match, name frequency, Latin-script indicator, IMO performance percentile, timing gaps between IMO participation and education milestones, field indicators (math, engineering) at each education level, 12 career sector indicators, and whether the candidate's institution, field, country, and employer match what is known about the participant from the LLM and manual coding.

2.2.4 Validation of University Coding

Appendix Tables A.2–A.4 report what predicts whether we could not find a medalist's institution: the miss rate is higher for earlier cohorts (27% for 1981–2000 vs. 14% for 2015–2020) and for participants from non-English-speaking countries.

We validated our combined university coding against two external administrative sources (see Appendix D). First, MIT's Registrar verified the full list of 2015–2020 medalists against enrollment records and confirmed that our combined coding (manual + LLM + LinkedIn) captures all MIT undergraduates, with zero missed placements. Second, we matched medalists against Cambridge University graduation yearbooks (2018–2023), where names appear as first initial plus surname. Our combined coding identifies 111 Cambridge medalists; yearbook matching found approximately 9 additional medalists not yet captured (adjusted for the 9.5% false-match rate among known non-Cambridge students). We interpret these results as evidence that our data collection captures nearly all medalists at the world's top universities.

3 How and Why Do IMO Medalists End Up Mismatched?

3.1 Do IMO Medalists Attend the Best Universities?

We focus on 2015–2020 medalists—the most recent cohort with complete data (descriptive statistics for the 1980–2000 and 2001–2014 cohorts appear in the Appendix)—to characterize where the world's top math talent goes to college. Using our combined Shanghai ranking (the better of the overall ARWU and the math subject ranking; see Section 2), we observe that at least 28% of medalists attended a top-10 university and at least 61% a top-500 institution. We could not find an undergraduate institution for 15% of medalists in this cohort, so the true shares may be higher.

To estimate the full distribution across all university ranks, we impute the remaining 15% of medalists using a simulation calibrated to our validation data. The imputation model exploits the rank-dependent miss rate implied by the MIT and Cambridge validation exercises (Section 2): MIT's enrollment is exact (zero missed medalists), Cambridge has nine additional medalists identified through yearbook matching, and other top-10 universities are inflated by the average MIT/Cambridge factor of 1.04. For universities ranked below the top 10, we allow the inflation factor to increase linearly with rank—reflecting the intuition, corroborated by validation, that medalists at lower-ranked institutions are harder to find online.[4] We convert these infla-

[4]Specifically, let n_r denote the observed number of medalists at rank r. For $r > 10$ we set the expected count to $\hat{n}_r = n_r \times (1 + 0.04\,\alpha\,(r-10))$, where α is calibrated so that the total expected count equals the number of

tion factors into sampling probabilities—$P(\text{missing} \to \text{rank } r) \propto \max N_r - N_r$—and draw 1,000 bootstrap samples, assigning each missing medalist to a rank according to these probabilities. Figure 1 displays the median cumulative allocation with 95% confidence bands: 29% of medalists attend a top-10 university [95% CI: 29–30%], 50% a top-100 [49–50%], and 70% a top-500 [69–71%]. Nearly a third of IMO medalists attend universities outside the top 500.

3.2 Who Ends Up Undermatched?

We estimate linear probability models of the form

$$\mathbf{1}[\text{Top-}j]_i = \alpha + \beta\, Perf_i + \phi\, Female_i + \lambda\, MigNeeded_i + \mathbf{Z}_i'\boldsymbol{\theta} + \eta_{t(i)} + \varepsilon_i \tag{1}$$

where $\mathbf{1}[\text{Top-}j]_i$ indicates whether participant i attends a top-j university ($j \in \{10, 50, 500\}$, scaled $\times 100$), $Perf_i$ is the participant's best IMO score percentile, $Female_i$ is a gender indicator, $MigNeeded_i$ indicates that the participant's country lacks a top-j university, $\mathbf{Z}_i$ is a vector of bilateral covariates (log GDP, distance to the US and UK, linguistic and cultural proximity, diplomatic and colonial ties), and $\eta_{t(i)}$ are last-competition-year fixed effects. In a baseline specification we replace $MigNeeded_i$ and $\mathbf{Z}_i$ with country-of-origin fixed effects. Table 2 reports results; two patterns emerge.

First, universities appear to select on observable characteristics. Higher-scoring medalists attend better universities regardless of specification, with each percentile of IMO performance associated with a 0.3–0.6pp increase in placement probability across all three tiers. Preferences could drive part of this gradient, but it is implausible that so many lower-scoring medalists would decline admission to a top university. Female medalists are 21–25pp more likely to attend a top-10 university, 19–22pp for top-50, and 15–17pp for top-500, conditional on performance and country—a gap consistent with universities' preferences for gender diversity in STEM rather than differential demand.

Second, country of origin is a strong predictor of placement—country fixed effects explain substantial variation (columns 1, 4, 7). When we replace them with observable country-level channels (columns 2–3, 5–6, 8–9), including log GDP, distance to the US and UK, linguistic and cultural proximity, and colonial ties, the strongest predictor for top-10 and top-50 placement is whether a medalist's country hosts such a university: needing to migrate is associated with a 36–40pp lower probability of top-10 placement and 36–43pp for top-50. For comparison, mov-

medalists ($\alpha = 0.015$). Because the inflation ratio is pinned at 1.04 by the MIT/Cambridge validation, the choice of functional form makes almost no difference: all must pass through the same boundary condition at the top, leaving little room for divergence over the narrow range of ranks.

ing across the full range of IMO performance observed among medalists—whose scores span roughly 48 percentiles, from 52 to 100, since all medalists are in the top half of participants—is associated with a 20–23pp change in top-10 placement and 19–25pp for top-50. The migration penalty is thus larger than the full performance range for both tiers. At the top-500 level the penalty is near zero and national income becomes the more relevant predictor—likely because over half of the countries in our sample have at least one top-500 institution. Appendix Tables A.8 and A.9 report analogous regressions for earlier periods; the top-50 migration penalty is similar in magnitude (32–47pp), though the top-500 penalty declines over time as more countries gain ranked universities.

The penalty falls disproportionately on participants from lower-income countries. No low-income country hosts a top-500 university, and among lower-middle-income countries only India, Georgia, Pakistan, and Vietnam do. Most participants from these income groups must therefore migrate to access a highly ranked institution. Bangladesh and several Sub-Saharan African nations send strong competitors but lack any top-ranked domestic option. By contrast, upper-middle-income countries such as China, Iran, and Turkey host one or more top-500 universities, offering a partial domestic alternative. The misallocation problem is thus most acute at the bottom of the global income distribution, where domestic alternatives are weakest and migration barriers are highest. Figure 2 displays the cumulative allocation separately by development status:[5] among developing-country medalists, only 24% attend a top-10 university, compared to near-universal placement among US and UK medalists. The gap is largest at the top of the ranking, precisely where the career-outcome associations documented in Section 4 are strongest.

Figure 3 illustrates. Among medalists whose undergraduate institution we identified, countries with top-50 universities (excluding the US and UK) place 69% of their bronze, 74% of their silver, and 93% of their gold medalists at top-50 institutions. Countries without top-50 universities place 28%, 40%, and 50%. 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—all US and UK bronze and silver medalists in our data attend a top-50 institution.[6]

This allocation has, however, improved over time. Figure 5 shows that the share of medalists at top-50 universities has risen steadily since the mid-2000s, driven largely by MIT and Cambridge.

[5]We define developing countries as non-high-income economies per the World Bank income classification, encompassing low-income, lower-middle-income, and upper-middle-income categories.

[6]These figures condition on finding a BA institution and are likely optimistic: medalists whose undergraduate institution we could not identify are disproportionately from countries without top-ranked universities and, within each country group, are more likely to have attended a lower-ranked institution. Both forces imply that the true gaps are wider than those shown.

3.3 Medals as Signals

Top universities may use IMO medals—instead of IMO score—as signals of ability. We test whether this friction contributes to the misallocation using a regression discontinuity design 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 each participant's maximum-ever distance to a medal.[7]

For IMO cohorts 2006–2020, the probability of attending a top-10 university changes smoothly with IMO performance, except possibly at the gold vs. silver threshold (Figure 4). At the bronze and silver thresholds there is no evidence of discontinuity: the RD estimates are 4.1pp (s.e. 4.6) and -3.0pp (s.e. 4.3), neither significant at any bandwidth from 20 to 10 percentiles of performance. At the gold threshold the point estimate is 10.9pp (s.e. 5.0, $p < 0.05$), ranging from 9.1pp at a bandwidth of 20 to 15.3pp at a bandwidth of 10—consistent with a discrete premium for the top distinction, though sensitive to bandwidth. Appendix Figures A.3 and A.4 show similar, but less pronounced and not statistically significant patterns for reaching top-50 and top-500 universities. In the earlier 1981–2005 period there is no evidence for any effect of medals on university quality (Appendix Figure A.2). These patterns are consistent with either (i) most universities selecting most students on their continuous score or (ii) most universities ignoring IMO performance completely, in favor of other measures of ability. Either way, the apparent discontinuity at the gold vs. silver threshold suggests that universities discard part of the IMO performance information, penalizing almost-golds relative to barely-golds.

To gauge how much medal-based screening could explain, suppose bronze and silver medalists received the same admissions premium as gold medalists: overall top-10 placement would rise by roughly 9pp—closing less than one-eighth of the gap between developing-country and US/UK medalists. Medal-based screening thus accounts for at most a small share of the undermatching documented above.

3.4 Migration Barriers and Financing

The mismatch is unlikely to reflect preferences for staying home. In a survey of STEM talent from developing countries, Agarwal et al. (2023) find that 81% of respondents report aspiring

[7] For instance, if a competitor participated twice, once placing two percentiles below a silver and once placing three percentiles above a silver, that participant would show up as barely getting a silver, with their running variable equal to three. For the bronze vs. no medal comparison, we do not use manually-inputted universities to avoid mechanical data collection effects. Appendix Figure A.1 confirms that medal receipt jumps sharply at each cutoff. See Section 2 for details on medal assignment and data construction.

to study in the US or UK. Yet among the 2015–2020 medalists from developing countries, only 29–34% actually study in the US or UK (the range reflects whether medalists with no identified institution are included). The gap implies that 47–52% of all developing-country medalists (about 50 per year) aspire to study in the US or UK but are unable to do so.

Financing appears to be the main barrier: survey data in Agarwal et al. (2023) show that 57% of STEM talent from developing countries cite cost as a very important reason for not applying to US universities. The sticker price for a four-year undergraduate degree at a top-10 university—approximately $360k including room and board—is prohibitive for most families outside wealthy countries. Financial aid for international students is uneven. MIT, the single largest destination for IMO medalists, offers need-blind financial aid regardless of nationality—admitting students without regard to their ability to pay, then meeting full demonstrated need. Harvard, Yale, Princeton, and Amherst follow the same policy. But most other top-10 universities—including Stanford, Caltech, Columbia, and Chicago—are need-aware for international applicants, meaning that ability to pay influences admission decisions. If all top-10 universities adopted MIT's need-blind policy, the financing constraint would largely dissolve for students with the academic credentials to gain admission. The improving allocation trend visible in Figure 5 is consistent with this: MIT and Cambridge—the two institutions driving the rise—both actively recruit IMO medalists and offer need-blind financial aid to international students. Indeed, among the 40 US and UK medalists for whom we found undergraduate institutions, all but one attended a top-10 university—bronze-level math talent suffices for admission; what separates placed from mismatched medalists is where they were born.

Undergraduate placement also shapes longer-run migration: a US or UK undergraduate education predicts an 18–23pp and 30pp higher probability of living in the US or UK later in life, respectively (Appendix Table A.11), a pattern Choudhury et al. (2023) also document among top JEE scorers in India.[8] For countries seeking to attract and retain top talent, undergraduate education is an entry point to the migration pipeline (Docquier and Rapoport, 2012).

4 Career Outcomes and Undermatching

Section 3 documented that a large share of the world's top math talent does not reach the best universities, with the need to migrate the strongest predictor of undermatching. Does the undermatch matter: does society lose anything of value, or would top talent produce the same

[8]The late-life location data were collected by Agarwal and Gaule (2020). The sample uses the 1980–2000 medalist cohort because late-life location requires sufficient time to have elapsed since graduation. Appendix Table A.10 reports a related outcome—whether the participant attended university abroad.

economic value regardless of which university it attends? Although we lack the exogenous variation in university attendance to answer this question, 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.[9] Sensitivity analyses also suggest that omitted factors are unlikely to explain away these associations. We focus on the four outcomes introduced in Section 1—top-10 PhD, major academic prize, leading technology firm, and founder/CEO—spanning science, technology, and entrepreneurship.

For this analysis, we expand the sample from medalists to all IMO participants, which increases our power and provides the variation in initial ability needed to explore whether university quality and talent may be complements (Section 4.4). 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 virtually all US/UK participants attend top-10 universities, leaving no variation in university tier within that group. We estimate:

$$Y_i = \sum_k \beta_k \mathbf{1}[\text{Tier}_i = k] \; + \; \mathbf{X}_i'\boldsymbol{\gamma} \; + \; \delta_{c(i)} \; + \; \eta_{t(i)} \; + \; \varepsilon_i \tag{2}$$

where Y_i is a career outcome for participant i (scaled $\times 100$ so coefficients are in percentage points), $\mathbf{1}[\text{Tier}_i = k]$ are indicators for the university tier of i's undergraduate institution (top 10, 11–50, 51–500, 501–1,000; omitted category: outside top 1,000 or university not found), $\mathbf{X}_i$ 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. The coefficients of interest are β_k: the association between attending a tier-k university and each outcome, conditional on ability, origin, and cohort. Participants whose undergraduate institution we could not find (55% of the sample) are either included in an additional university tier ("BA not found" in the tables, i.e., undergraduate institution not identified) or dropped; we present both specifications. All outcomes are binary; logit average marginal effects (Appendix Tables A.23 and A.24) confirm the same sign, significance, and ranking across tiers. Point estimates are attenuated for low-prevalence outcomes—top-10 PhD: 11pp vs. 32pp in the LPM—because the nonlinear logit specification mechanically shrinks average marginal effects with many fixed effects. For higher-prevalence outcomes, logit and LPM estimates are similar (in-math: -7pp vs. -7pp; base rate

[9] Natural experiments, such as the dissolution of the Soviet Union or shifts in US immigration restriction, could help identify the effects of increased access to top universities. Nevertheless, the "first stage" generated by these natural experiments was too weak or delayed in relation to the event, so we do not include such estimates in the paper. Similarly, the medal cutoffs examined in Section 3.3 do not generate variation in university placement in this cohort (Appendix Figure A.2).

25%).

4.1 Career Outcomes and University Quality

Table 3 reports OLS estimates of university tier indicators on four career outcomes, all expressed in percentage points (pp). Relative to participants outside the top 1,000, attending a top-10 university is associated with a 32pp increase in the probability of earning a PhD from a top-10 institution, a 7pp increase in working at a leading technology firm,[10] and a 5pp increase in becoming a founder or CEO (all $p < 0.01$). For major prizes—the union of LLM-reported recognitions and curated prize-list matching (Section 2.2.2)—the point estimate is 12pp ($p < 0.01$), nearly doubling the sample average. These coefficients are large relative to sample averages of 9% (top-10 PhD), 12% (major prizes), 4% (leading tech firm), and 7% (founder/CEO).[11]

The gradient across university tiers is monotonic for academic outcomes. Attending a top 11–50 university is associated with a 6pp increase in top-10 PhD rates—substantial, but roughly one-fifth the top-10 coefficient. Below the top 50, associations with PhD placement weaken further. For industry outcomes (leading tech firm, founder/CEO), only top-10 and top 11–50 universities show significant associations.

Restricting to the $N = 2{,}693$ participants for whom we found an undergraduate institution (columns 2, 4, 6, 8) yields somewhat smaller coefficients—28pp for top-10 PhD, 7pp for leading tech firm—but all remain large and significant. The decrease is expected: participants with an identified undergraduate institution are positively selected on career visibility, so the omitted category in this subsample is stronger, compressing the gap.

A limitation of the tier specification is that university rank and university country are heavily confounded: most top-10 universities are in the US or UK, so the tier coefficients may capture access to US/UK labor markets, networks, or visa pathways rather than university quality per se. Appendix Table A.14 explores this by replacing tier indicators with destination-country indicators. Both the US and UK predict stronger academic trajectories and leading tech firm employment, but only the US predicts founder/CEO outcomes—consistent with a broader US startup ecosystem. Appendix Figures A.5 and A.6 show that the association is broad-based across top-10 institutions, not driven by a single university.

[10] 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.

[11] These magnitudes are broadly comparable to quasi-experimental estimates: Chetty et al. (2025) find that Ivy-Plus attendance nearly doubles elite graduate school rates, and Zimmerman (2019) finds a 51% increase in reaching the top 0.1% of income from elite enrollment in Chile.

4.2 Robustness to Selection on Unobservables

The concern is that participants who attend top universities differ on unobserved dimensions—family wealth, ambition, preparation—that independently predict career outcomes. We assess sensitivity to such confounding using the framework of Cinelli and Hazlett (2020), which asks: how strongly associated with both treatment and outcome—in terms of partial R^2—would an unobserved confounder need to be to explain away the estimated association?

We make two adjustments to the baseline specification for this analysis. First, we sharpen the comparison by dropping participants at intermediate-tier universities (ranks 11–500), comparing top-10 attendees directly against those outside the top 500. Second, we replace country fixed effects with interpretable country-level channels—log GDP per capita, English-speaking share, and linguistic distance—so that these covariates can serve as benchmarks for the sensitivity analysis. This substitution barely changes the estimates (e.g., 32.4pp vs. 33.3pp for top-10 PhD; Appendix Table A.12), suggesting that the country channels capture the same variation as the fixed effects. Table 4 reports the results for career outcomes; Table 7 does so for field sorting.

Benchmark-free robustness values. The robustness value $\text{RV}_{q=1}$ reports the minimum partial R^2 a confounder would need with *both* treatment and outcome to reduce the estimate to zero. For the two core academic outcomes, these thresholds are high: $\text{RV}_{q=1} = 25.3\%$ for top-10 PhD and 8.1% for major prizes—a confounder would need to explain 25% of residual variation for top-10 PhD, or 8% for major prizes, in both university attendance and the outcome. Industry outcomes have lower but non-trivial thresholds: 8.8% for leading tech firm, 6.8% for finance, and 4.1% for founder/CEO. For field sorting, the in-academia robustness value (7.2%) is comparable to the industry outcomes, while in-math (5.7%) is more fragile but survives at the 5% level ($\text{RV}_{q=1,\alpha=.05} = 2.8\%$).

Benchmarked adjustments. The framework also asks: if an unobserved confounder were k times as strongly associated with treatment and outcome as some observed covariate, how much would the estimate change? Panel A of Tables 4 and 7 benchmarks against IMO performance—the strongest individual-level predictor of both university attendance and career outcomes. Even at three times the confounding strength of IMO performance, all associations retain their sign (e.g., top-10 PhD drops from 32.4 to 27.6pp, prizes from 10.4 to 5.9pp), though in-math is attenuated nearly to zero (-10.3 to 0.1pp).

Panel B benchmarks against the combined country channels. At $3\times$ country channels, the top-10 PhD estimate drops from 32.4 to 31.0pp, prizes from 10.4 to 9.1pp, leading tech firm from 7.8 to 6.7pp, founder/CEO from 4.6 to 1.8pp, and finance from 8.7 to 5.0pp—all associations survive. The country-FE specification (Appendix Table A.12) provides a more conserva-

tive benchmark; even there, the PhD association survives at 20.5pp.

The two most plausible confounders are family wealth and ambition.

Wealth and preparation. Family wealth plausibly predicts top-10 attendance (ability to pay tuition, legacy connections) and some career outcomes (startup capital, professional networks). Pre-university preparation (coaching and advanced training) can also raise admission chances and later productivity. But both mechanisms predict, if anything, the wrong sign on field sorting. Wealthier individuals can better afford to pursue lower-paying academic careers than poorer individuals of the same ability, while stronger preparation raises comparative advantage in math. Under this logic, if wealth and preparation drive both university placement and outcomes, top-10 attendees should be, if anything, *more* likely to remain in math and academia, not less. We find the opposite: top-10 attendance is associated with a shift *away* from math and *toward* finance (Section 4.3).

Ambition. Domain-general ambition—a drive to maximize career success regardless of field—could predict top-10 attendance, prize-winning, and high-earning careers simultaneously. But this creates a tension with the joint pattern of field sorting and prizes. Top-10 attendees are less likely to work in academia—the sector that produces the academic prizes in our data—yet more likely to win prizes. If ambitious individuals sort into top-10 universities and are then redirected toward finance, the pool of potential prizewinners among top-10 attendees shrinks. For prize rates to *increase* despite this compositional shift, a parsimonious explanation is that university quality adds something—mentorship, peers, research exposure—that more than compensates for the reduced mass in the prize-producing sector.

Neither wealth nor ambition rationalizes the joint pattern of field sorting and prizes. Wealth and preparation predict, if anything, the wrong sign on field sorting; ambition predicts the right sign but cannot generate higher prize rates while thinning the prize-producing pool. The pattern is more consistent with a role of university quality in talent development than with pure selection alone. We formalize this in Appendix E: under pure selection, explaining both field sorting (fewer in academia) and higher prize rates requires the confound's intensive-margin effect on research productivity to exceed its extensive-margin effect on academic exit—a restrictive condition that neither candidate naturally satisfies (Proposition 1).

4.3 Field Sorting

Beyond within-field associations, top-10 attendance predicts different career paths. Conditional on ability and country, attending a top-10 university predicts a 9pp decrease in the probability of working in academia ($p < 0.01$), a 7pp decrease in math specifically ($p < 0.05$), and a 9pp increase in finance ($p < 0.01$; Table 6).

This redirection is not driven by who selects into top-10 universities. Without controls, the raw correlations between top-10 attendance and both academia (+20pp) and math (+7pp) careers are *positive* (Appendix Table A.13). Both flip to negative after controlling for IMO performance, gender, and country—indicating that high-ability participants stay in academia regardless, but top-10 attendance is associated with a shift toward finance for those on the margin. The robustness values for the in-academia and in-math coefficients are 7.2% and 5.7%, respectively, and both sign reversals survive benchmarking against country-level channels at three times their observed strength (adjusted estimates: -3.4pp and -2.1pp; Table 7).

This redirection does not come at a cost to scientific output. As shown in Section 4.1, top-10 attendance is associated with *higher* academic prize rates despite the shift away from academia. This combination—fewer people in academia, yet more prizes—is difficult to explain through selection and is most consistent with a role for university quality in raising the productivity of those who remain in research.

4.4 Heterogeneity by Ability

We interact university tier indicators with IMO performance quartiles to test whether the association between university quality and outcomes varies with initial ability (Table 5).

For academic outcomes, the association with top-10 attendance increases with ability. The top-10 PhD premium rises from 21pp for the lowest performance quartile to 33pp for the highest ($p < 0.01$ for all quartiles). For prizes, the association is concentrated in the top quartile: 10pp ($p < 0.01$), with a smaller, statistically insignificant 6pp for the 50th–75th percentile and near-zero estimates for lower quartiles. This pattern suggests that the mismatch documented in Section 3 matters most at the top of the talent distribution, where the potential gains from better placement are largest—consistent with the academic-match effects documented by Dillon and Smith (2020) for degree completion and earnings.

For industry outcomes, the pattern differs. The leading tech firm and founder/CEO premiums are largest for the 25th–50th percentile (13pp and 14pp, respectively; $p < 0.01$) and small at both extremes (3–5pp, largely insignificant). The association with top-10 attendance is strongest for industry careers among participants with moderate—rather than exceptional—math talent, consistent with comparative advantage: the highest-ability participants have the strongest returns in academia, while moderate-ability participants gain most from the industry networks and career paths that top universities provide.

5 Discussion

We document that roughly 71% of IMO medalists attend universities outside the top 10. Country of origin is the dominant predictor of this mismatch, reducing the probability of attending a top-10 institution by 36–40pp for students who would need to migrate. The mismatch is associated with large differences in career outcomes: top-10 attendance predicts a 32pp increase in earning a top-10 PhD, a 12pp increase in winning a major academic prize, a 7pp increase in working at a leading technology firm, and a 5pp increase in founding a company. Top-10 attendance also predicts a shift away from academia and toward finance—yet academic prize rates are *higher* among top-10 attendees, a combination that is difficult to reconcile with selection alone. Sensitivity analysis (Cinelli and Hazlett, 2020) indicates that a confounder would need to explain 8–25% of residual variation in both treatment and outcome to nullify the core academic estimates. The association between university quality and academic outcomes increases with ability, while the industry premium is largest for moderate-ability participants—consistent with comparative advantage shaping how top universities sort talent across fields. The misallocation we document—where country of origin rather than gender or race is the binding constraint—parallels settings where talent reallocation has large aggregate effects: declining occupational barriers for women and minorities explain 20–40% of US output growth since 1960 (Hsieh et al., 2019), and the influx of émigré scientists from Nazi Germany raised US patenting by 31% in their fields (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 misallocation documented here represents not only a private cost but a social one: foregone scientific discoveries, technological contributions, and new firms.

Several limitations apply. Our career outcome data rely on online traces—LLM-extracted biographies and LinkedIn profiles—which are more complete for participants who achieved visible careers. We address this by including a "BA not found" indicator in all regressions and showing that results are similar when restricting to those with an identified undergraduate institution, but differential visibility across countries remains a concern. Our causal argument rests on coefficient stability and cross-outcome consistency rather than an instrument; while we attempted several IV strategies (exchange rate instruments, Bartik shift-share, pipeline IV), none produced a credible first stage. While we cannot pin down a causal effect, the combination of high robustness values for the core academic outcomes (25% for top-10 PhD, 8% for major prizes), precise ability controls, and a cross-outcome pattern that wealth or ambition are unlikely to rationalize sets a high bar for a purely selection-based explanation.

The financing barrier is tractable. Roughly 134 medalists per year attend universities outside the top 10; adjusting for the 19% who do not aspire to study in the US or UK (Agarwal et al., 2023), the target population is approximately 110 students per year, at a cost of roughly $39 million annually. The Global Talent Fund's BIG scholarship demonstrates that this barrier can be overcome: in its first two cohorts, BIG placed 78 science olympiad medalists from 30 countries at top universities in the UK and France. The annual cost is less than 1% of first-year enrollment at top-10 universities and a fraction of their existing financial aid budgets—modest relative to the potential returns from placing the world's most mathematically talented students at institutions equipped to develop that talent.

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Main Tables and Figures

Table 1: Descriptive Statistics for IMO 2015-2020 Medalists

Variable	Mean	Standard Deviation	Observations
Unknown Undergraduate Institution	0.14	0.35	1,132
MIT or Cambridge	0.21	0.40	1,132
Top 10 University	0.28	0.45	1,132
Top 50 University	0.39	0.49	1,132
Top 500 University	0.61	0.49	1,132
Top 1000 University	0.72	0.45	1,132
Silver Medal	0.35	0.48	1,132
Gold Medal	0.19	0.40	1,132
Developing Countries	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

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

	Dependent variable:								
	Top 10 university			Top 50 university			Top 500 university		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Best Performance Percentile (0-100)	0.42***	0.43***	0.47***	0.39***	0.50***	0.52***	0.26*	0.54***	0.64***
	(0.12)	(0.10)	(0.11)	(0.14)	(0.10)	(0.12)	(0.14)	(0.11)	(0.11)
Female	21.37***	24.90***	28.32***	18.58***	21.81***	23.58***	15.33**	17.35***	17.85***
	(6.51)	(6.09)	(6.32)	(6.48)	(6.02)	(6.13)	(6.00)	(5.73)	(5.30)
Would Need to Migrate		−36.18***	−40.07***		−36.37***	−42.75***		−7.92**	−5.06
		(5.78)	(5.93)		(3.69)	(3.77)		(3.91)	(4.18)
Low Income		−20.16***	−17.50		−23.51***	−19.62*		−43.98***	−28.30*
		(5.68)	(11.57)		(6.03)	(11.65)		(9.98)	(16.93)
Middle Income		−2.75	−5.24*		3.19	0.34		−15.26***	−23.80***
		(2.73)	(3.09)		(3.05)	(3.30)		(3.22)	(3.15)
Dep. var mean	28.27	28.27	33.06	39.4	39.4	46.07	61.31	61.31	71.69
Country FEs	Yes	No	No	Yes	No	No	Yes	No	No
Sample	All	All	BA Found	All	All	BA Found	All	All	BA Found
Observations	1,132	1,132	968	1,132	1,132	968	1,132	1,132	968
R^2	0.34	0.13	0.15	0.36	0.16	0.19	0.35	0.10	0.14

Notes: Linear probability models. The dependent variable is an indicator ($\times 100$) for attending a university at or above the indicated rank threshold (combined Shanghai ARWU overall and math subject ranking). "Would Need to Migrate" equals one if the participant's country hosts no university (overall or math) at or above the threshold. Income groups are World Bank classifications of the country of origin, collapsed to low, middle (lower- and upper-middle), and high; high income is the omitted group. Column 1 (4, 7) includes country-of-origin fixed effects; columns 2–3 (5–6, 8–9) drop them. All specifications include IMO participation count and last-competition-year fixed effects. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Robust (HC3) standard errors in parentheses.

Table 3: Career Outcomes and University Tier (Non-US/UK IMO Participants, Last Competition $\leq$ 2005)

	Dependent variable:							
	Top 10 PhD	Top 10 PhD	Major prize	Major prize	Leading tech firm	Leading tech firm	Founder/CEO	Founder/CEO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top 10 BA	32.02***	27.75***	12.00***	10.65***	7.17***	6.73***	5.09***	6.34**
	(1.98)	(2.86)	(2.36)	(3.52)	(1.51)	(2.22)	(1.93)	(2.70)
Top 11-50 BA	5.62***	4.60	5.07**	3.27	4.35***	5.45**	−1.29	−1.91
	(1.98)	(3.04)	(2.36)	(3.73)	(1.51)	(2.35)	(1.93)	(2.87)
Top 51-500 BA	4.30***	2.56	7.00***	4.27	−0.18	1.35	−1.59	1.18
	(1.41)	(2.28)	(1.68)	(2.80)	(1.07)	(1.76)	(1.37)	(2.15)
Top 501-1000 BA	2.01	−4.98*	4.21*	0.05	−1.06	−0.57	−1.75	−0.31
	(1.93)	(2.98)	(2.30)	(3.66)	(1.47)	(2.31)	(1.88)	(2.81)
BA not found	−5.77***		−14.46***		−4.97***		−10.00***	
	(1.13)		(1.35)		(0.86)		(1.10)	
Sample	All	BA found	All	BA found	All	BA found	All	BA found
Dep. var mean	8.89	16.64	12.31	23.99	4.28	8.02	7.03	11.99
N	5928	2693	5928	2693	5928	2693	5928	2693
R^2	0.21	0.21	0.16	0.10	0.09	0.11	0.07	0.08

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4: Sensitivity to Unobserved Confounding: Career Outcomes (Cinelli & Hazlett 2020, Non-US/UK, Country Channels)

	Est. (pp)	SE	t	$R^2_{Y\sim D\|\mathbf{X}}$	$\text{RV}_{q=1}$	$\text{RV}_{q=1,\alpha=.05}$	Adjusted estimate 1×	2×	3×
Panel A: Benchmark = IMO performance (linear + quadratic)									
Top-10 PhD	32.4	(1.7)	19.33	7.9%	25.3%	23.1%	30.8	29.2	27.6
Major Prize	10.4	(1.9)	5.55	0.7%	8.1%	5.3%	8.9	7.4	5.9
Leading Tech Firm	7.8	(1.3)	6.05	0.8%	8.8%	6.0%	7.3	6.8	6.2
Founder/CEO	4.6	(1.7)	2.74	0.2%	4.1%	1.2%	3.9	3.3	2.6
Panel B: Benchmark = Country channels (log GDP/cap + English share + language distance)									
Top-10 PhD	32.4	(1.7)	19.33	7.9%	25.3%	23.1%	31.9	31.5	31.0
Major Prize	10.4	(1.9)	5.55	0.7%	8.1%	5.3%	10.0	9.5	9.1
Leading Tech Firm	7.8	(1.3)	6.05	0.8%	8.8%	6.0%	7.4	7.1	6.7
Founder/CEO	4.6	(1.7)	2.74	0.2%	4.1%	1.2%	3.7	2.8	1.8

Sensitivity analysis following Cinelli and Hazlett (2020). Sample: Non-US/UK IMO participants, last competition $\leq$ 2005, restricted to top-10 vs. outside-500 (ranks 11–500 dropped). Treatment: attended a top-10 university. Controls: IMO performance (linear and quadratic), gender, log GDP per capita, English-speaking share, language distance, cohort FE, BA-not-found indicator, and number of IMO participations. Outcomes in percentage points. $R^2_{Y\sim D|\mathbf{X}}$: partial R^2 of top-10 with outcome. $\text{RV}_{q=1}$: 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 to destroy significance at 5%. Adjusted estimates show the bias-corrected coefficient if an unobserved confounder were k times as strongly associated with treatment and outcome as the benchmark covariate. Panel A benchmarks against IMO performance (linear and quadratic, grouped); Panel B benchmarks against Country channels (log GDP/cap + English share + language distance).

Table 5: Heterogeneous Returns: Performance Quartile × University Tier (Non-US/UK, Last Competition ≤ 2005)

	Dependent variable:							
	Top 10 PhD		Major Prize		Leading Tech Firm		Founder/CEO	
	All	BA found	All	BA found	All	BA found	All	BA found
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Perf 0-25 x Top 10 BA	21.57***	17.43***	1.59	1.58	3.32	1.23	5.11	2.37
	(4.85)	(6.76)	(5.78)	(8.31)	(3.70)	(5.24)	(4.74)	(6.39)
Perf 25-50 x Top 10 BA	17.46***	14.58***	−2.03	−0.06	12.75***	11.51***	14.18***	13.63***
	(3.91)	(5.34)	(4.65)	(6.57)	(2.98)	(4.14)	(3.81)	(5.05)
Perf 50-75 x Top 10 BA	29.69***	27.19***	6.15	6.26	7.22***	5.09	6.88*	6.23
	(3.60)	(4.88)	(4.28)	(6.00)	(2.74)	(3.78)	(3.51)	(4.61)
Perf 75-100 x Top 10 BA	32.79***	29.71***	9.95***	12.31**	3.04	0.56	3.15	2.60
	(2.91)	(4.03)	(3.46)	(4.96)	(2.22)	(3.13)	(2.84)	(3.82)
Perf 0-25 x Top 500 BA	0.93	3.11	2.91	8.20*	−1.14	0.39	0.01	−0.06
	(2.17)	(3.62)	(2.58)	(4.45)	(1.65)	(2.80)	(2.11)	(3.42)
Perf 25-50 x Top 500 BA	1.38	0.64	0.85	−0.32	2.54*	4.39*	−2.03	−2.79
	(1.94)	(3.30)	(2.31)	(4.06)	(1.48)	(2.56)	(1.90)	(3.12)
Perf 50-75 x Top 500 BA	3.68**	4.76	3.09	3.82	1.62	3.00	0.33	1.84
	(1.80)	(3.10)	(2.14)	(3.81)	(1.37)	(2.40)	(1.76)	(2.93)
Perf 75-100 x Top 500 BA	7.73***	8.40***	11.09***	4.73	1.18	2.29	−2.01	2.58
	(1.72)	(3.08)	(2.04)	(3.79)	(1.31)	(2.39)	(1.68)	(2.91)
BA not found	−6.60***		−15.98***		−4.63***		−9.43***	
	(0.98)		(1.17)		(0.75)		(0.96)	
Sample	All	BA found	All	BA found	All	BA found	All	BA found
Dep. var mean	8.89	16.64	12.31	23.99	4.28	8.02	7.03	11.99
N	5928	2693	5928	2693	5928	2693	5928	2693
Observations	5,928	2,693	5,928	2,693	5,928	2,693	5,928	2,693
R^2	0.21	0.22	0.16	0.10	0.09	0.12	0.07	0.08
Note:	*p<0.1; **p<0.05; ***p<0.01							

Table 6: Field Sorting: Academia, Math, and Finance by University Tier (Non-US/UK, Last Competition $\leq$ 2005)

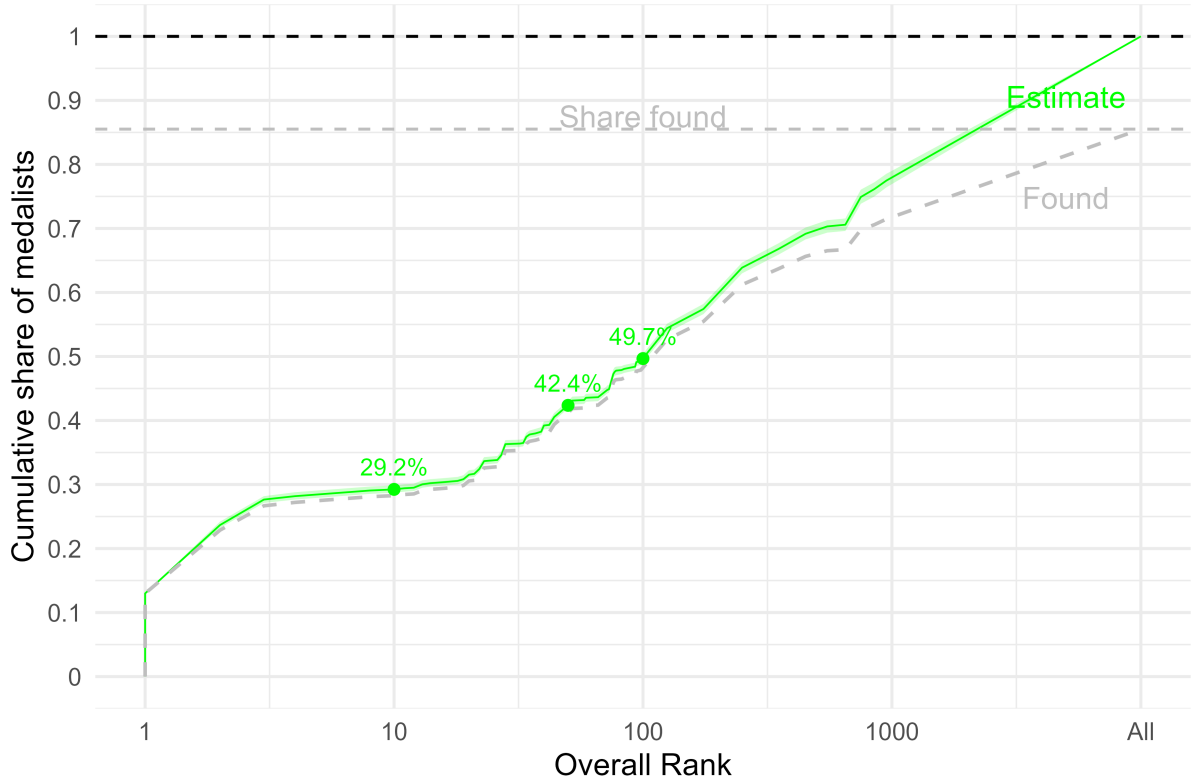
	Dependent variable:					
	In Academia	In Academia	In Math	In Math	Finance job	Finance job
	(1)	(2)	(3)	(4)	(5)	(6)
Top 10 BA	-8.65^{***}	-7.43^{**}	-7.35^{**}	-5.50	9.33^{***}	11.44^{***}
	(3.14)	(3.42)	(3.01)	(3.89)	(2.13)	(2.99)
Top 11-50 BA	-6.03^{*}	-0.15	-5.54^{*}	-3.84	3.63^{*}	6.83^{**}
	(3.14)	(3.63)	(3.00)	(4.12)	(2.12)	(3.17)
Top 51-500 BA	1.86	4.56^{*}	6.43^{***}	4.62	-3.44^{**}	0.98
	(2.23)	(2.72)	(2.13)	(3.09)	(1.51)	(2.38)
Top 501-1000 BA	2.26	0.76	-0.09	1.26	-4.21^{**}	-3.26
	(3.06)	(3.56)	(2.93)	(4.05)	(2.07)	(3.12)
BA not found	-46.55^{***}		-21.92^{***}		-12.65^{***}	
	(1.79)		(1.72)		(1.21)	
Sample	All	BA found	All	BA found	All	BA found
Dep. var mean	47.67	76.05	24.93	40.25	8.81	15.26
N	5928	2693	5928	2693	5928	2693
R^2	0.35	0.15	0.21	0.16	0.08	0.08
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 7: Sensitivity to Unobserved Confounding: Field Sorting (Cinelli & Hazlett 2020, Non-US/UK, Country Channels)

	Est. (pp)	SE	t	$R^2_{Y\sim D\|\mathbf{X}}$	$\text{RV}_{q=1}$	$\text{RV}_{q=1,\alpha=.05}$	Adjusted estimate 1×	2×	3×
Panel A: Benchmark = IMO performance (linear + quadratic)									
In Academia	-15.1	(3.1)	-4.90	0.5%	7.2%	4.4%	-11.3	-7.5	-3.6
In Math	-10.3	(2.7)	-3.86	0.3%	5.7%	2.8%	-6.9	-3.4	0.1
In Finance	8.7	(1.9)	4.67	0.5%	6.8%	4.0%	8.2	7.8	7.3
Panel B: Benchmark = Country channels (log GDP/cap + English share + language distance)									
In Academia	-15.1	(3.1)	-4.90	0.5%	7.2%	4.4%	-11.3	-7.4	-3.4
In Math	-10.3	(2.7)	-3.86	0.3%	5.7%	2.8%	-7.6	-4.9	-2.1
In Finance	8.7	(1.9)	4.67	0.5%	6.8%	4.0%	7.5	6.2	5.0

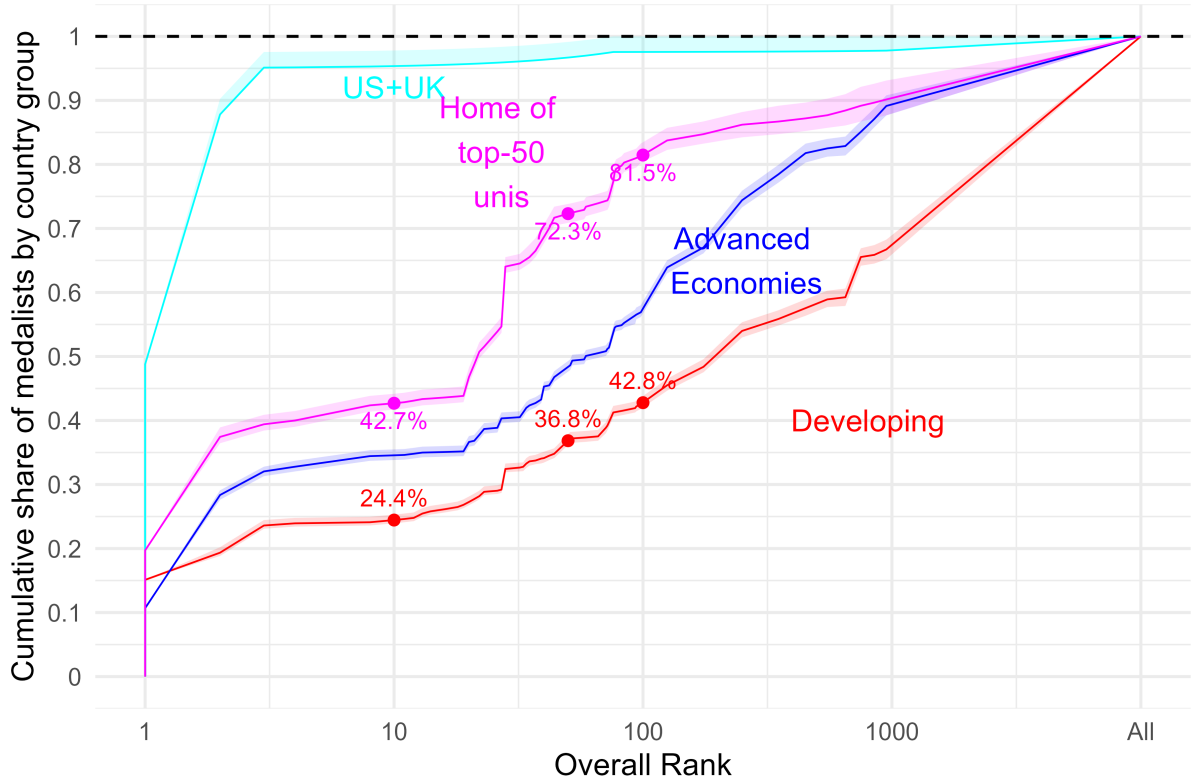
Sensitivity analysis following Cinelli and Hazlett (2020). Sample: Non-US/UK IMO participants, last competition $\leq$ 2005, restricted to top-10 vs. outside-500 (ranks 11–500 dropped). Treatment: attended a top-10 university. Controls: IMO performance (linear and quadratic), gender, log GDP per capita, English-speaking share, language distance, cohort FE, BA-not-found indicator, and number of IMO participations. Outcomes in percentage points. $R^2_{Y\sim D|\mathbf{X}}$: partial R^2 of top-10 with outcome. $\text{RV}_{q=1}$: 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 to destroy significance at 5%. Adjusted estimates show the bias-corrected coefficient if an unobserved confounder were k times as strongly associated with treatment and outcome as the benchmark covariate. Panel A benchmarks against IMO performance (linear and quadratic, grouped); Panel B benchmarks against Country channels (log GDP/cap + English share + language distance).

Figure 1: Cumulative Share of Medalists by University Rank



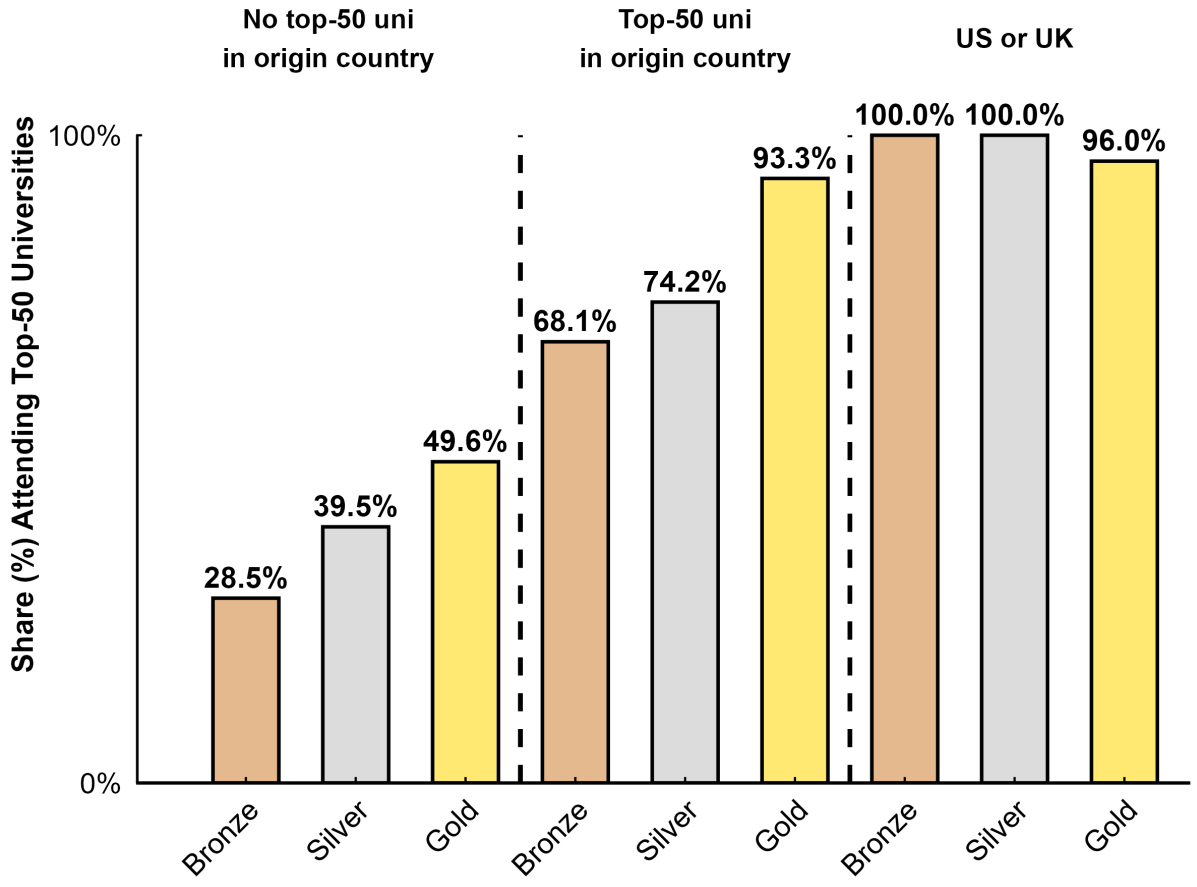
Notes: Cumulative share of IMO medalists (2015–2020, $N = 1{,}132$) attending a university at or above each combined Shanghai (ARWU) rank (the better of the overall and math subject ranking). Grey dashed line: medalists with a "BA found" (i.e., undergraduate institution identified) only. Green solid line: 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). Green shaded area: 95% confidence band. Horizontal grey dashed line marks the share of medalists with BA found (85.5%). Percentage annotations show the median cumulative share at the top-10, top-50, and top-100 thresholds.

Figure 2: Misallocation by Development Status



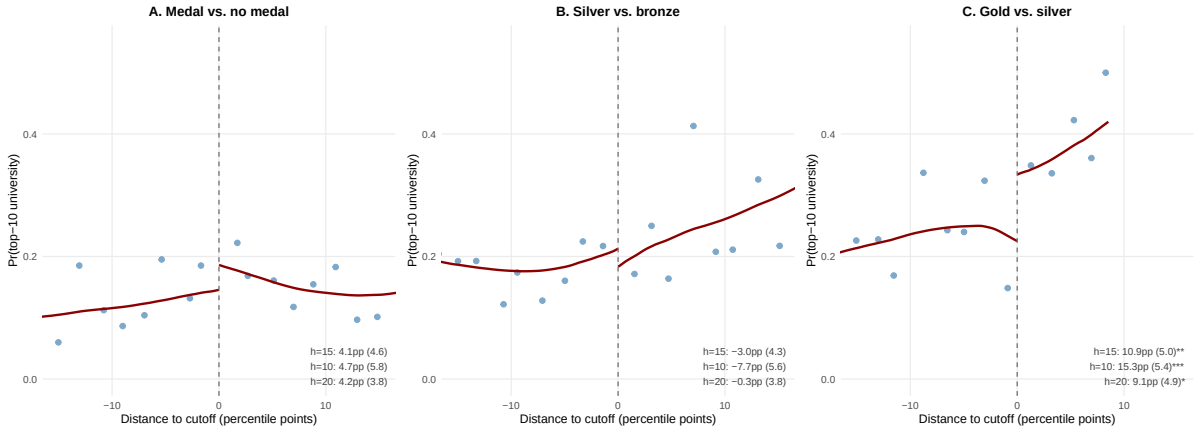
Notes: Cumulative estimated share of IMO medalists (2015–2020, $N = 1{,}132$) attending a university at or above each combined Shanghai (ARWU) rank, by origin country group. Solid lines: median allocation from 1,000 simulation draws (see Figure 1 notes); shaded areas: 95% confidence bands. "Developing": non-high-income economies per World Bank classification. "Advanced Economies": high-income countries excluding US and UK. "US+UK": medalists from the United States or United Kingdom. "Home of top-50 unis": medalists from countries hosting at least one top-50 Shanghai-ranked university. Percentage annotations show cumulative shares at the top-10, top-50, and top-100 thresholds for developing countries (red) and countries with top-50 universities (magenta).

Figure 3: Country of Origin Matters More Than Medals



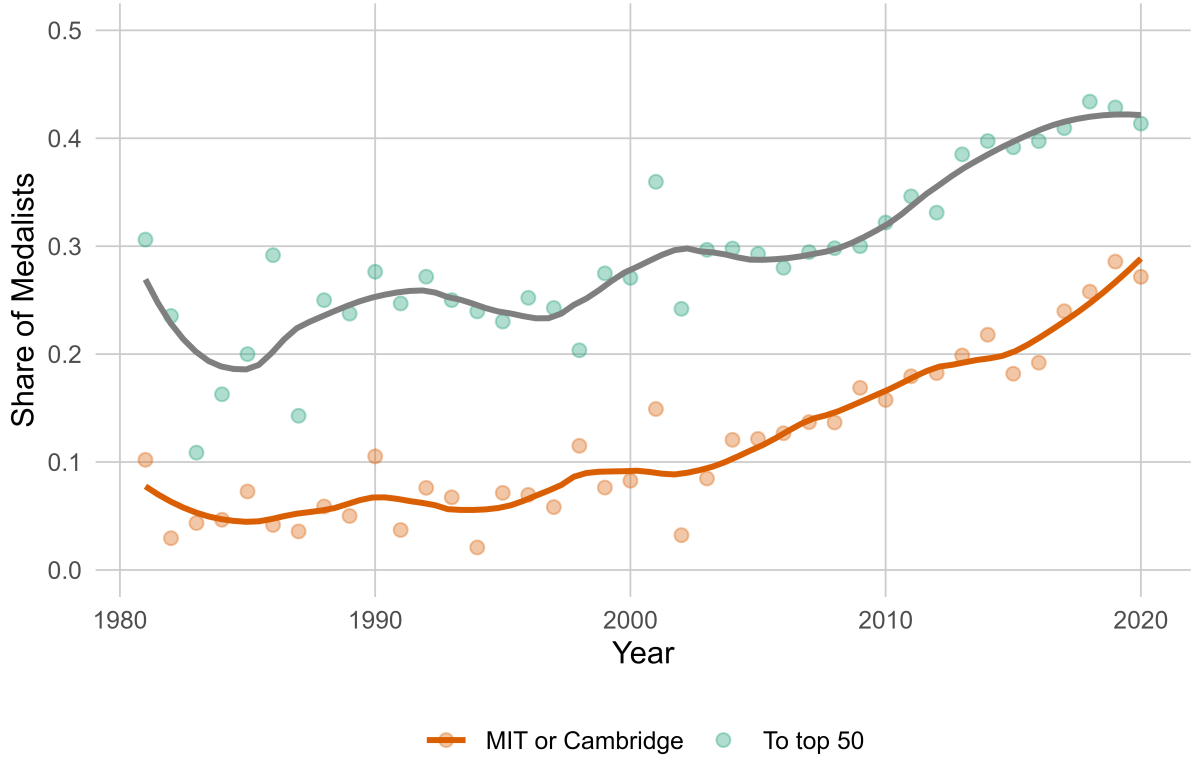
Notes: Share of IMO medalists (2015–2020) attending a top-50 Shanghai-ranked university, by medal type and origin country group. Sample restricted to medalists with BA found ($N = 967$). Three mutually exclusive groups: "No top-50 uni in origin country" ($n = 747$) denotes medalists from countries without a top-50 Shanghai-ranked university; "Top-50 uni in origin country" ($n = 180$) denotes medalists from countries hosting at least one top-50 university, excluding US and UK; "US or UK" ($n = 40$). Bar widths are proportional to each medal type's share within its country group.

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 Shanghai-ranked university. Each panel plots binned means (2-percentile-point bins) and a local linear fit within a fixed bandwidth of 15 percentile points on each side of the cutoff. The running variable is the participant's maximum distance (in percentile points) to the year-specific medal threshold across all IMO participations; 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 2006–2020 IMO participants ($N = 5{,}292$); panels B and C use the medalist sample ($N = 2{,}750$), which has more complete university data from manual coding.

Figure 5: Misallocation Is Improving Over the Long Run

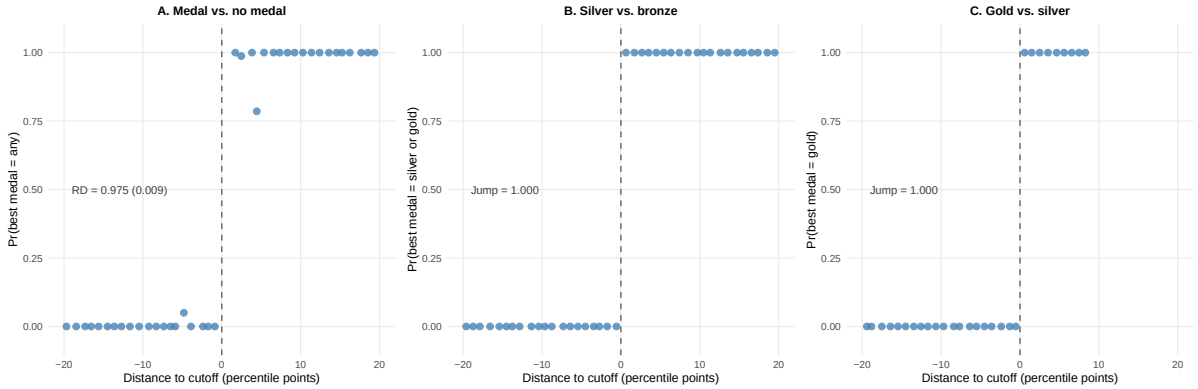


Notes: Share of IMO medalists attending a top-50 Shanghai-ranked university (green) or MIT/Cambridge specifically (orange), by last year of IMO participation (1981–2020). Sample restricted to medalists with BA found. Points show annual shares; curves are loess-smoothed (span = 0.3). Both series trend upward from the mid-2000s, with the top-50 share rising from roughly 25% to over 40% by 2020.

Appendices

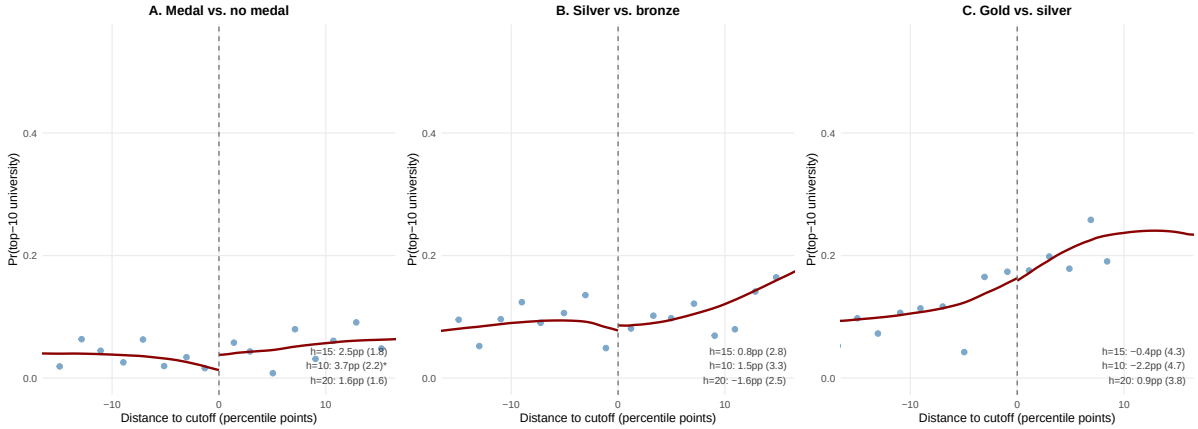
A Additional Figures

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



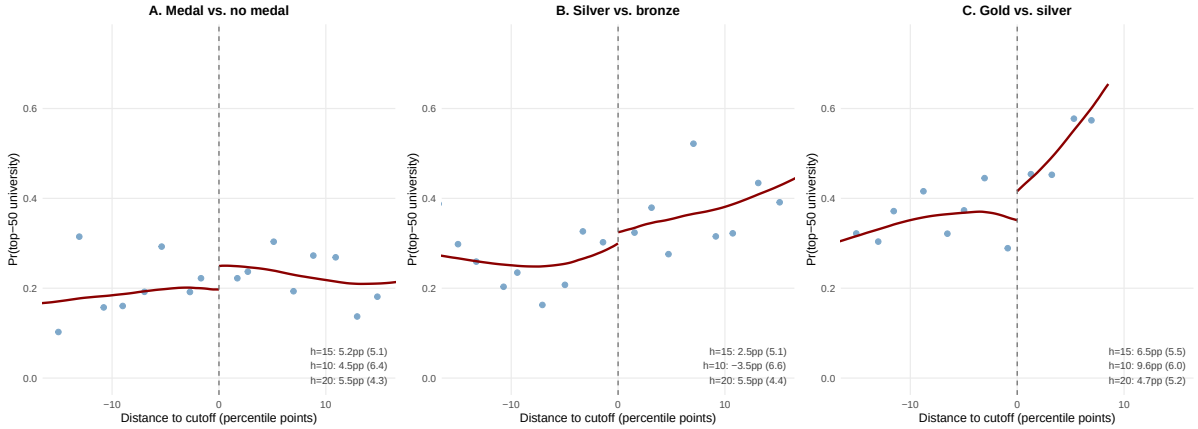
Notes: First-stage regression discontinuity plots showing that medal receipt jumps sharply at each cutoff. The outcome is an indicator for receiving the relevant medal (or better). The running variable is the participant's maximum distance (in percentile points) to the year-specific medal threshold across all IMO participations. Binned means and linear fits on each side of the cutoff. 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, confirming that medal assignment follows the score rule. Sample: all 2006–2020 IMO participants.

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



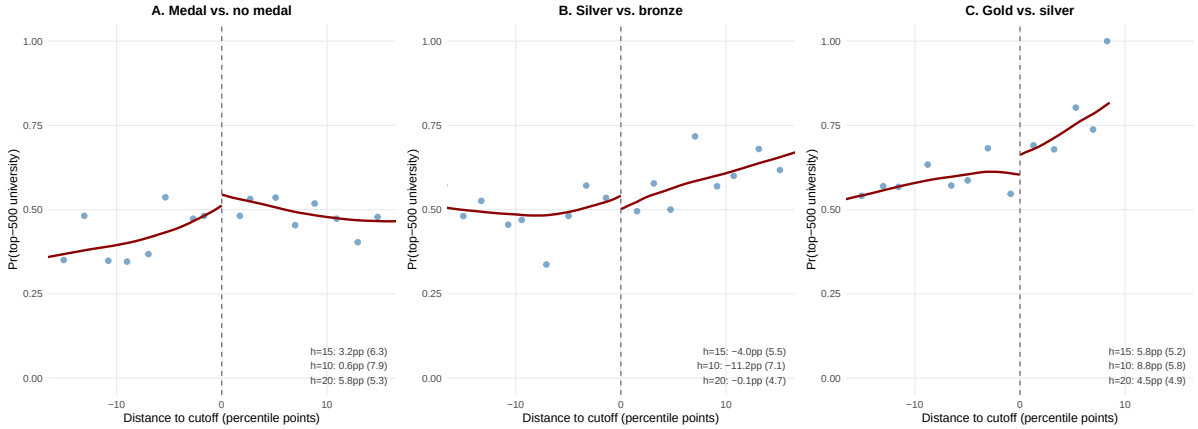
Notes: Same specification as Figure 4 but for 1981–2005 IMO participants ($N = 6{,}132$). Local linear fits within a fixed bandwidth of 15 percentile points on each side of the cutoff. None of the three RD estimates is significant: 1.6pp (s.e. 2.8) for bronze, 0.1pp (s.e. 2.1) for silver, and 1.4pp (s.e. 3.1) 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.

B Additional Tables

Table A.1: Universities Classified as "Top 10" and "Top 11–50"

University	Country	Overall	Math	Combined
Panel A: Top 10 (14 universities)				
Massachusetts Institute of Technology	US	1	6	1
Princeton University	US	6	1	1
University of Cambridge	UK	2	5	2
Paris-Saclay University	France	15	2	2
Harvard University	US	3	29	3
University of Oxford	UK	7	3	3
Stanford University	US	4	9	4
Sorbonne University	France	46	4	4
University of California, Berkeley	US	5	26	5
Université Paris Cité	France	69	7	7
ETH Zurich	Switzerland	20	8	8
Columbia University	US	8	17	8
California Institute of Technology	US	9	47	9
University of Chicago	US	10	25	10
Panel B: Top 11–50 (selected universities attended by IMO participants)				
Yale University	US	11	39	11
Stony Brook University	US	301	11	11
New York University	US	28	12	12
Cornell University	US	12	51	12
EPFL	Switzerland	54	13	13
University of California, Los Angeles	US	13	15	13
Rutgers University	US	101	14	14
University of Pennsylvania	US	14	101	14
Johns Hopkins University	US	16	101	16
University of Wisconsin–Madison	US	35	16	16
University College London	UK	17	51	17
University of Toronto	Canada	24	19	19
PSL University	France	41	20	20
University of Warwick	UK	101	21	21
Tsinghua University	China	22	38	22
Hebrew University of Jerusalem	Israel	86	22	22
University of Bonn	Germany	67	23	23
Imperial College London	UK	23	24	23
University of Michigan–Ann Arbor	US	26	30	26
The University of Tokyo	Japan	27	51	27
Peking University	China	29	28	28

Notes: "Overall" is the 2024 Shanghai ARWU overall ranking; "Math" is the 2024 Shanghai ARWU mathematics subject ranking. "Combined" is the better (lower) of the two. A university is classified as "top N" if its combined rank is $\leq N$. Because the combined ranking takes the better of two lists, more than 10 universities qualify as "top 10" and more than 40 as "top 11–50." Panel B shows the 21 most frequently attended top 11–50 universities among IMO participants; the full tier contains 45 distinct universities in our data.

Table A.2: What Predicts Us Not Finding their Current Institution (IMO 2015-2020 Medalists)

	Dependent variable:		
	Unknown Undergraduate Institution		
	(1)	(2)	(3)
Best Performance (50-100)	−0.157	−0.071	−0.069
	(0.105)	(0.079)	(0.079)
Female	−3.311	−3.042	−2.776
	(4.531)	(4.341)	(4.381)
Developing Country		−2.285	−7.232**
		(2.123)	(3.027)
Engl. Speakers Share			−12.672***
			(4.712)
Dep. var mean	14.49	14.49	14.49
Country FEs	Yes	No	No
Observations	1,132	1,132	1,132
R^2	0.215	0.005	0.012
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.3: What Predicts Us Not Finding their Current Institution (IMO 1981-2000 Medalists)

	Dependent variable:		
	Unknown Undergraduate Institution		
	(1)	(2)	(3)
Best Performance (50-100)	−0.425***	−0.357***	−0.388***
	(0.075)	(0.063)	(0.063)
Female	−9.391**	−6.930	−6.379
	(4.413)	(4.215)	(4.239)
Developing Country		5.659***	−6.180**
		(1.901)	(3.111)
Engl. Speakers Share			−24.669***
			(4.780)
Dep. var mean	26.78	26.78	26.78
Country FEs	Yes	No	No
Observations	2,252	2,252	2,250
R^2	0.166	0.042	0.054
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.4: What Predicts Us Not Finding their Current Institution (IMO 2001-2014 Medalists)

	Dependent variable:		
	Unknown Undergraduate Institution		
	(1)	(2)	(3)
Best Performance (50-100)	-0.193^{***}	-0.138^{***}	-0.160^{***}
	(0.063)	(0.052)	(0.052)
Female	-1.154	-1.658	-0.751
	(3.177)	(3.140)	(3.113)
Developing Country		-1.998	-10.175^{***}
		(1.513)	(2.162)
Engl. Speakers Share			-19.984^{***}
			(3.557)
Dep. var mean	15.79	15.79	15.79
Country FEs	Yes	No	No
Observations	2,400	2,400	2,390
R^2	0.138	0.016	0.030
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.5: Descriptive Statistics for IMO 1980-2000 Medalists

Variable	Mean	Standard Deviation	Observations
Unknown Undergraduate Institution	0.27	0.44	2,252
MIT or Cambridge	0.05	0.22	2,252
Top 10 University	0.10	0.30	2,252
Top 50 University	0.22	0.41	2,252
Top 500 University	0.47	0.50	2,252
Top 1000 University	0.59	0.49	2,252
Silver Medal	0.34	0.47	2,252
Gold Medal	0.18	0.39	2,252
Developing Countries	0.58	0.49	2,252
Low Income	0.12	0.32	2,252
Lower Middle Income	0.27	0.44	2,252
Upper Middle Income	0.20	0.40	2,252
Female	0.04	0.21	2,252

Table A.6: Descriptive Statistics for IMO 1990-2010 Medalists

Variable	Mean	Standard Deviation	Observations
Unknown Undergraduate Institution	0.20	0.40	3,215
MIT or Cambridge	0.08	0.27	3,215
Top 10 University	0.14	0.35	3,215
Top 50 University	0.26	0.44	3,215
Top 500 University	0.48	0.50	3,215
Top 1000 University	0.62	0.49	3,215
Silver Medal	0.33	0.47	3,215
Gold Medal	0.19	0.39	3,215
Developing Countries	0.60	0.49	3,215
Low Income	0.10	0.30	3,215
Lower Middle Income	0.30	0.46	3,215
Upper Middle Income	0.21	0.40	3,215
Female	0.05	0.22	3,215

Table A.7: Descriptive Statistics for IMO 2001-2014 Medalists

Variable	Mean	Standard Deviation	Observations
Unknown Undergraduate Institution	0.16	0.36	2,400
MIT or Cambridge	0.12	0.33	2,400
Top 10 University	0.19	0.40	2,400
Top 50 University	0.30	0.46	2,400
Top 500 University	0.52	0.50	2,400
Top 1000 University	0.65	0.48	2,400
Silver Medal	0.34	0.47	2,400
Gold Medal	0.21	0.40	2,400
Developing Countries	0.57	0.49	2,400
Low Income	0.07	0.25	2,400
Lower Middle Income	0.24	0.43	2,400
Upper Middle Income	0.26	0.44	2,400
Female	0.06	0.23	2,400

Table A.8: Predictors of University Placement (IMO 1980–2000 Medalists)

	Dependent variable:								
	Top 10 university			Top 50 university			Top 500 university		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Best Performance Percentile (0-100)	0.004	0.06	0.01	0.13**	0.25***	0.23***	0.31***	0.58***	0.54***
	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.07)	(0.08)	(0.07)	(0.08)
Female	3.27	2.57	2.37	10.42***	5.08	2.25	12.47***	10.87**	7.97
	(2.91)	(3.04)	(3.73)	(3.42)	(3.84)	(4.52)	(4.34)	(4.82)	(5.08)
Would Need to Migrate		−43.05***	−52.64***		−37.45***	−46.35***		−19.42***	−21.80***
		(3.41)	(3.85)		(2.58)	(3.05)		(2.59)	(3.51)
Low Income		−2.24	−3.05		4.74*	7.77**		−29.48***	−31.87***
		(1.46)	(2.17)		(2.87)	(3.59)		(3.29)	(3.96)
Middle Income		0.75	0.78		0.18	−0.85		−27.93***	−37.10***
		(1.19)	(1.60)		(2.14)	(2.75)		(2.30)	(2.42)
Dep. var mean	10.12	10.12	13.83	21.94	21.94	29.96	46.63	46.63	63.67
Country FEs	Yes	No	No	Yes	No	No	Yes	No	No
Sample	All	All	BA Found	All	All	BA Found	All	All	BA Found
Observations	2,252	2,252	1,649	2,252	2,252	1,649	2,252	2,252	1,649
R^2	0.38	0.21	0.25	0.40	0.20	0.25	0.38	0.16	0.23

Notes: Linear probability models. The dependent variable is an indicator ($\times 100$) for attending a university at or above the indicated rank threshold (combined Shanghai ARWU overall and math subject ranking). "Would Need to Migrate" equals one if the participant's country hosts no university (overall or math) at or above the threshold. Income groups are World Bank classifications of the country of origin, collapsed to low, middle (lower- and upper-middle), and high; high income is the omitted group. Column 1 (4, 7) includes country-of-origin fixed effects; columns 2–3 (5–6, 8–9) drop them. All specifications include IMO participation count and last-competition-year fixed effects. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Robust (HC3) standard errors in parentheses.

Table A.9: Predictors of University Placement (IMO 2001–2014 Medalists)

	Dependent variable:								
	Top 10 university			Top 50 university			Top 500 university		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Best Performance Percentile (0-100)	0.26***	0.37***	0.38***	0.33***	0.44***	0.44***	0.36***	0.57***	0.60***
	(0.07)	(0.06)	(0.06)	(0.08)	(0.06)	(0.07)	(0.09)	(0.07)	(0.07)
Female	9.12***	9.82***	11.61***	9.83***	9.74**	10.65**	7.19**	6.55	6.21
	(3.27)	(3.75)	(4.23)	(3.68)	(4.08)	(4.52)	(3.51)	(4.15)	(4.35)
Would Need to Migrate		−39.10***	−45.56***		−41.52***	−49.63***		−16.15***	−15.55***
		(3.98)	(4.25)		(2.59)	(2.68)		(2.51)	(2.83)
Low Income		−6.89***	−5.03		−5.27	−0.84		−35.92***	−36.56***
		(2.63)	(3.82)		(3.31)	(4.72)		(4.03)	(5.33)
Middle Income		−0.87	−2.35		0.71	−1.36		−21.98***	−30.79***
		(1.71)	(1.97)		(1.98)	(2.18)		(2.23)	(2.23)
Dep. var mean	19.42	19.42	23.06	30.12	30.12	35.77	52.42	52.42	62.25
Country FEs	Yes	No	No	Yes	No	No	Yes	No	No
Sample	All	All	BA Found	All	All	BA Found	All	All	BA Found
Observations	2,400	2,400	2,021	2,400	2,400	2,021	2,400	2,400	2,021
R^2	0.34	0.13	0.15	0.38	0.20	0.25	0.41	0.17	0.22

Notes: Linear probability models. The dependent variable is an indicator (×100) for attending a university at or above the indicated rank threshold (combined Shanghai ARWU overall and math subject ranking). "Would Need to Migrate" equals one if the participant's country hosts no university (overall or math) at or above the threshold. Income groups are World Bank classifications of the country of origin, collapsed to low, middle (lower- and upper-middle), and high; high income is the omitted group. Column 1 (4, 7) includes country-of-origin fixed effects; columns 2–3 (5–6, 8–9) drop them. All specifications include IMO participation count and last-competition-year fixed effects. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Robust (HC3) standard errors in parentheses.

Table A.10: Undergraduate Education and Undergraduate Migration (IMO 1980 - 2000 Medalists, Excluding US and UK Medalists)

	Dependent variable:			
	Studied Abroad			
	(1)	(2)	(3)	(4)
Undergrad. in the US or UK	0.247***	0.192***	0.170***	0.133***
	(0.041)	(0.045)	(0.042)	(0.047)
Best Performance (50-100)		0.004***		0.004***
		(0.001)		(0.001)
Dep. var mean				
Sample	All	All	BA Found	BA Found
Country and Year FEs	No	Yes	No	Yes
Observations	2,035	2,035	1,480	1,480
R^2	0.023	0.155	0.012	0.162

Note: *p<0.1; **p<0.05; ***p<0.01. The dependent variable equals one if the participant's undergraduate university is in a different country from their IMO country of origin.

Table A.11: Undergraduate Education and Late-life Migration to US and UK (IMO 1980 - 2000 Medalists, Excluding US and UK Medalists)

	Dependent variable:			
	Migrant to US		Migrant to UK	
	(1)	(2)	(3)	(4)
Undergrad. in the US	0.229***	0.176***	0.006	0.018
	(0.042)	(0.046)	(0.015)	(0.019)
Undergrad. in the UK	−0.102***	−0.085*	0.299***	0.305***
	(0.037)	(0.044)	(0.092)	(0.092)
Best Performance (50-100)		0.003***		0.0003
		(0.001)		(0.0003)
Dep. var mean	0.15	0.15	0.03	0.03
Country and Year FEs	No	Yes	No	Yes
Observations	2,102	2,102	2,102	2,102
R^2	0.027	0.148	0.044	0.087

Note: *p<0.1; **p<0.05; ***p<0.01. Late-life location is coded from biography notes compiled by research assistants during manual data collection.

Table A.12: Sensitivity to Unobserved Confounding (Cinelli & Hazlett 2020, Non-US/UK, Top-10 vs. Outside 500)

	Est. (pp)	SE	t	$R^2_{Y\sim D\|\mathbf{X}}$	$\text{RV}_{q=1}$	$\text{RV}_{q=1,\alpha=.05}$	Adjusted estimate 1×	2×	3×
Panel A: Benchmark = IMO performance (linear + quadratic)									
Top-10 PhD	33.3	(1.7)	19.87	8.2%	25.8%	23.6%	33.0	32.7	32.4
Major Prize	11.1	(1.9)	5.80	0.8%	8.4%	5.6%	10.8	10.5	10.2
Leading Tech Firm	8.6	(1.3)	6.58	1.0%	9.4%	6.7%	8.5	8.4	8.4
Founder/CEO	5.8	(1.7)	3.36	0.3%	4.9%	2.1%	5.7	5.5	5.4
In Math	-7.4	(2.7)	-2.75	0.2%	4.1%	1.2%	-6.9	-6.3	-5.7
In Finance	10.0	(1.9)	5.30	0.6%	7.7%	4.9%	9.9	9.7	9.5
In Academia	-9.2	(3.1)	-3.00	0.2%	4.4%	1.5%	-8.6	-8.0	-7.4
Panel B: Benchmark = Country of origin									
Top-10 PhD	33.3	(1.7)	19.87	8.2%	25.8%	23.6%	20.5	5.3	-13.5
Major Prize	11.1	(1.9)	5.80	0.8%	8.4%	5.6%	1.0	-11.0	-25.9
Leading Tech Firm	8.6	(1.3)	6.58	1.0%	9.4%	6.7%	1.4	-7.1	-17.6
Founder/CEO	5.8	(1.7)	3.36	0.3%	4.9%	2.1%	-3.5	-14.6	-28.3
In Math	-7.4	(2.7)	-2.75	0.2%	4.1%	1.2%	12.3	35.8	64.9
In Finance	10.0	(1.9)	5.30	0.6%	7.7%	4.9%	0.5	-10.8	-24.8
In Academia	-9.2	(3.1)	-3.00	0.2%	4.4%	1.5%	18.4	51.2	91.9

Sensitivity analysis following Cinelli and Hazlett (2020). Sample: Non-US/UK IMO participants, last competition $\leq$ 2005, restricted to top-10 vs. outside-500 (ranks 11–500 dropped). Treatment: attended a top-10 university. Controls: IMO performance (linear and quadratic), gender, country FE, cohort FE, BA-not-found indicator, and number of IMO participations. Outcomes in percentage points. $R^2_{Y\sim D|\mathbf{X}}$: partial R^2 of top-10 with outcome. $\text{RV}_{q=1}$: 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 to destroy significance at 5%. Adjusted estimates show the bias-corrected coefficient if an unobserved confounder were k times as strongly associated with treatment and outcome as the benchmark covariate. Panel A benchmarks against IMO performance (linear and quadratic, grouped); Panel B benchmarks against Country of origin.

Table A.13: Field Sorting: Raw vs. Conditional Associations (Non-US/UK, Last Competition $\leq$ 2005)

	Dependent variable:					
	In Academia		In Math		In Finance	
	Raw	Conditional	Raw	Conditional	Raw	Conditional
	(1)	(2)	(3)	(4)	(5)	(6)
Top 10 BA	19.979***	−8.875***	6.573**	−9.216***	15.987***	10.769***
	(3.199)	(2.825)	(2.779)	(2.708)	(1.809)	(1.915)
Controls	No	Yes	No	Yes	No	Yes
Country FE	No	Yes	No	Yes	No	Yes
Cohort FE	No	Yes	No	Yes	No	Yes
Dep. var. mean	47.7	47.7	24.9	24.9	8.8	8.8
Observations	5,928	5,928	5,928	5,928	5,928	5,928
R^2	0.007	0.354	0.001	0.209	0.013	0.078

Note: *p<0.1; **p<0.05; ***p<0.01
Outcomes in percentage points. Conditional specification includes IMO performance (linear and quadratic), gender, country FE, cohort FE, number of IMO participations, and BA-not-found indicator. Sample: non-US/UK IMO participants, last competition $\leq$ 2005.

Table A.14: Career Outcomes by Destination Country (Non-US/UK IMO Participants, Last Competition $\leq$ 2005)

	Dependent variable:							
	Top 10 PhD	Top 10 PhD	Major prize	Major prize	Leading tech firm	Leading tech firm	Founder/CEO	Founder/CEO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
US BA	23.44***	21.49***	9.41***	9.85***	7.43***	7.17***	5.83***	6.46***
	(1.84)	(2.63)	(2.19)	(3.22)	(1.40)	(2.03)	(1.79)	(2.48)
UK BA	33.97***	32.16***	8.50**	8.58	5.83**	5.75*	0.85	1.34
	(3.16)	(4.45)	(3.75)	(5.45)	(2.40)	(3.43)	(3.07)	(4.19)
Non-US/UK Top 500 BA	3.26***	3.61*	5.87***	4.51*	0.34	1.36	−0.86	0.82
	(1.25)	(2.03)	(1.48)	(2.49)	(0.95)	(1.57)	(1.21)	(1.91)
BA not found	−6.26***		−15.35***		−4.82***		−9.30***	
	(1.00)		(1.18)		(0.76)		(0.97)	
Sample	All	BA found	All	BA found	All	BA found	All	BA found
Dep. var mean	8.89	16.64	12.31	23.99	4.28	8.02	7.03	11.99
N	5928	2693	5928	2693	5928	2693	5928	2693
R^2	0.20	0.21	0.16	0.10	0.09	0.11	0.07	0.08

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.15: Robustness to LinkedIn Match Score Threshold — Main OLS (Top-10 BA Coefficient)

	Top 25%	Top 70% (baseline)	Top 100%
Major Prize	13.53***	12.00***	12.24***
	(3.52)	(3.25)	(3.16)
Top-10 PhD	34.41***	32.02***	30.98***
	(3.46)	(3.29)	(3.22)
Leading Tech Firm	5.65**	7.17***	8.81***
	(2.35)	(2.45)	(2.45)
Founder/CEO	4.58*	5.09*	5.88**
	(2.70)	(2.70)	(2.73)
In Academia	-8.41**	-8.65**	-8.48**
	(3.58)	(3.41)	(3.34)
In Math	-7.24**	-7.35**	-6.86**
	(3.52)	(3.30)	(3.25)
In Finance	9.77***	9.33***	7.24**
	(3.09)	(3.06)	(3.01)
N	5,928	5,928	5,928
% with LinkedIn	20.9%	72.6%	97.5%

Table A.16: Robustness to LinkedIn Match Score Threshold — Sensitivity Analysis (Cinelli & Hazlett 2020)

	Top 25%			Top 70% (baseline)			Top 100%		
	Est. (pp)	$RV_{q=1}$	Adj. 1×	Est. (pp)	$RV_{q=1}$	Adj. 1×	Est. (pp)	$RV_{q=1}$	Adj. 1×
Top-10 PhD	35.9	27.1%	35.6	33.3	25.8%	33.0	32.2	25.2%	31.8
Major Prize	12.6	9.0%	12.2	11.1	8.4%	10.8	11.3	8.6%	10.9
Leading Tech Firm	6.9	8.6%	6.8	8.6	9.4%	8.5	9.9	10.6%	9.8
Founder/CEO	4.9	4.3%	4.8	5.8	4.9%	5.7	6.7	5.5%	6.5
In Academia	-9.2	4.2%	-8.5	-9.2	4.4%	-8.6	-9.5	4.6%	-8.7
In Math	-7.5	3.9%	-6.7	-7.4	4.1%	-6.9	-7.1	3.9%	-6.4
In Finance	10.3	8.2%	10.1	10.0	7.7%	9.9	8.4	6.2%	8.1
N		4,672			4,551			4,493	
% with LinkedIn		16.9%			72.3%			97.0%	

Sample: Non-US/UK IMO participants, last competition $\leq$ 2005, top-10 vs. outside-500 (ranks 11–500 dropped). Est.: OLS coefficient on top-10 BA in percentage points. $RV_{q=1}$: minimum partial R^2 of a confounder with both treatment and outcome needed to reduce the estimate to zero. Adj. 1×: bias-adjusted estimate if confounder is as strong as IMO performance (linear + quadratic). Threshold = share of LinkedIn matches retained by random forest classifier.

Table A.17: Robustness to LinkedIn Match Score Threshold — Field Sorting (Top-10 BA Coefficient)

	Top 25%	Top 70% (baseline)	Top 100%
Panel A: Raw correlation (no controls)			
In Academia	24.19***	19.98***	18.76***
	(3.16)	(3.03)	(2.97)
In Math	9.26***	6.57**	6.47**
	(3.17)	(2.97)	(2.92)
In Finance	15.93***	15.99***	14.59***
	(2.78)	(2.71)	(2.65)
Panel B: With full controls			
In Academia	-8.41**	-8.65**	-8.48**
	(3.58)	(3.41)	(3.34)
In Math	-7.24**	-7.35**	-6.86**
	(3.52)	(3.30)	(3.25)
In Finance	9.77***	9.33***	7.24**
	(3.09)	(3.06)	(3.01)
N	5,928	5,928	5,928

Sample: Non-US/UK IMO participants, last competition $\leq$ 2005. Panel A: bivariate regression of field indicator on top-10 BA. Panel B: full specification with university tier dummies (top 10, 11–50, 51–500, 501–1000), BA-not-found, gender, IMO performance (linear + quadratic), country FE, cohort FE, IMO participations. Robust standard errors (HC1) in parentheses.

Table A.18: Robustness to LinkedIn Match Score Threshold — Assortative Matching (Performance × Top-10 Interactions)

Major Prize			
	Top 25%	Top 70% (baseline)	Top 100%
Perf 0–25 × Top 10	3.16	2.31	3.08
	(7.73)	(6.96)	(6.97)
Perf 25–50 × Top 10	-3.22	-3.11	-2.22
	(5.77)	(5.17)	(5.17)
Perf 50–75 × Top 10	9.39	6.93	8.29
	(6.74)	(6.05)	(5.86)
Perf 75–100 × Top 10	17.41***	16.01***	13.95***
	(5.28)	(5.08)	(4.85)
N	5,928	5,928	5,928
Top-10 PhD			
	Top 25%	Top 70% (baseline)	Top 100%
Perf 0–25 × Top 10	24.31***	20.99***	21.30***
	(8.81)	(8.01)	(8.00)
Perf 25–50 × Top 10	16.30**	17.29***	17.65***
	(6.59)	(6.22)	(6.23)
Perf 50–75 × Top 10	33.55***	31.32***	29.50***
	(7.09)	(6.63)	(6.43)
Perf 75–100 × Top 10	40.32***	37.14***	34.41***
	(5.03)	(4.99)	(4.88)
N	5,928	5,928	5,928
Leading Tech Firm			
	Top 25%	Top 70% (baseline)	Top 100%
Perf 0–25 × Top 10	1.50	1.93	2.14
	(4.59)	(4.82)	(4.77)
Perf 25–50 × Top 10	10.82**	14.39***	14.57***
	(5.15)	(5.46)	(5.48)
Perf 50–75 × Top 10	9.09*	8.10*	8.75*
	(4.89)	(4.64)	(4.62)
Perf 75–100 × Top 10	3.50	3.61	5.95
	(3.24)	(3.57)	(3.67)
N	5,928	5,928	5,928
Founder/CEO			
	Top 25%	Top 70% (baseline)	Top 100%
Perf 0–25 × Top 10	2.22	5.48	5.44
	(6.29)	(6.45)	(6.44)
Perf 25–50 × Top 10	12.99**	12.88**	12.74**
	(6.03)	(5.76)	(5.77)
Perf 50–75 × Top 10	7.50	7.34	6.02
	(5.50)	(5.24)	(5.03)
Perf 75–100 × Top 10	1.08	2.07	6.01*
	(3.16)	(3.27)	(3.65)
N	5,928	5,928	5,928

Sample: Non-US/UK IMO participants, last competition < 2005. Coefficients on performance quartile ×

Table A.19: Robustness to Dropping Common Names — Main OLS (Top-10 BA Coefficient)

	Full sample	Drop top 10% common names
Major Prize	12.00***	12.81***
	(3.25)	(3.44)
Top-10 PhD	32.02***	33.43***
	(3.29)	(3.43)
Leading Tech Firm	7.17***	7.10***
	(2.45)	(2.53)
Founder/CEO	5.09*	6.51**
	(2.70)	(2.87)
In Academia	-8.65**	-8.44**
	(3.41)	(3.61)
In Math	-7.35**	-7.59**
	(3.30)	(3.46)
In Finance	9.33***	8.97***
	(3.06)	(3.19)
N	5,928	5,330

Table A.20: Robustness to Dropping Common Names — Sensitivity Analysis (Cinelli & Hazlett 2020)

	Full sample			Drop top 10% common names		
	Est. (pp)	$RV_{q=1}$	Adj. 1×	Est. (pp)	$RV_{q=1}$	Adj. 1×
Top-10 PhD	33.3	25.8%	33.0	34.5	26.6%	34.2
Major Prize	11.1	8.4%	10.8	12.2	9.1%	12.0
Leading Tech Firm	8.6	9.4%	8.5	8.4	9.3%	8.4
Founder/CEO	5.8	4.9%	5.7	7.3	6.1%	7.2
In Academia	-9.2	4.4%	-8.6	-9.0	4.3%	-8.5
In Math	-7.4	4.1%	-6.9	-7.4	4.0%	-6.9
In Finance	10.0	7.7%	9.9	9.8	7.4%	9.7
N		4,551			4,129	

Sample: Non-US/UK IMO participants, last competition $\leq$ 2005, top-10 vs. outside-500. "Drop top 10% common names" excludes participants whose standardized name appears more than 41 times in LinkedIn data. Est.: OLS coefficient on top-10 BA (pp). $RV_{q=1}$: robustness value. Adj. 1×: bias-adjusted estimate benchmarked against IMO performance.

Table A.21: Robustness to Dropping Common Names — Field Sorting (Top-10 BA Coefficient)

	Full sample	Drop top 10% common names
Panel A: Raw correlation (no controls)		
In Academia	19.98***	19.21***
	(3.03)	(3.19)
In Math	6.57**	6.17**
	(2.97)	(3.13)
In Finance	15.99***	15.43***
	(2.71)	(2.83)
Panel B: With full controls		
In Academia	-8.65**	-8.44**
	(3.41)	(3.61)
In Math	-7.35**	-7.59**
	(3.30)	(3.46)
In Finance	9.33***	8.97***
	(3.06)	(3.19)
N	5,928	5,330

Sample: Non-US/UK IMO participants, last competition $\leq$ 2005. "Drop top 10% common names" excludes participants whose standardized name appears more than 41 times in LinkedIn data. Robust standard errors (HC1) in parentheses.

Table A.22: Robustness to Dropping Common Names — Assortative Matching (Performance × Top-10 Interactions)

Major Prize		
	Full sample	Drop top 10% common names
Perf 0–25 × Top 10	2.31	4.19
	(6.96)	(7.45)
Perf 25–50 × Top 10	-3.11	-3.71
	(5.17)	(5.41)
Perf 50–75 × Top 10	6.93	6.73
	(6.05)	(6.29)
Perf 75–100 × Top 10	16.01***	18.78***
	(5.08)	(5.41)
N	5,928	5,330
Top-10 PhD		
	Full sample	Drop top 10% common names
Perf 0–25 × Top 10	20.99***	24.25***
	(8.01)	(8.64)
Perf 25–50 × Top 10	17.29***	16.36**
	(6.22)	(6.44)
Perf 50–75 × Top 10	31.32***	30.60***
	(6.63)	(6.82)
Perf 75–100 × Top 10	37.14***	41.43***
	(4.99)	(5.11)
N	5,928	5,330
Leading Tech Firm		
	Full sample	Drop top 10% common names
Perf 0–25 × Top 10	1.93	-0.23
	(4.82)	(4.43)
Perf 25–50 × Top 10	14.39***	15.32***
	(5.46)	(5.70)
Perf 50–75 × Top 10	8.10*	9.58*
	(4.64)	(4.91)
Perf 75–100 × Top 10	3.61	3.51
	(3.57)	(3.65)
N	5,928	5,330
Founder/CEO		
	Full sample	Drop top 10% common names
Perf 0–25 × Top 10	5.48	6.83
	(6.45)	(6.91)
Perf 25–50 × Top 10	12.88**	15.71**
	(5.76)	(6.28)
Perf 50–75 × Top 10	7.34	9.33*
	(5.24)	(5.57)
Perf 75–100 × Top 10	2.07	2.36
	(3.27)	(3.50)
N	5,928	5,330

Sample: Non-US/UK IMO participants, last competition $<$ 2005. "Drop top 10% common names" excludes

Table A.23: Logit Average Marginal Effects: Career Outcomes (Non-US/UK, Last Competition $\leq$ 2005)

	Dependent variable:							
	Top 10 PhD	Top 10 PhD	Major prize	Major prize	Leading tech firm	Leading tech firm	Founder/CEO	Founder/CEO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top 10 BA	10.63***	19.24***	5.31***	10.38***	2.31**	5.39***	2.92**	5.70**
	(1.35)	(2.43)	(1.74)	(3.33)	(1.00)	(1.93)	(1.42)	(2.45)
Top 11–50 BA	2.67	6.92**	1.17	3.64	1.83	5.37**	-0.71	-1.82
	(1.65)	(3.05)	(1.87)	(3.65)	(1.14)	(2.24)	(1.60)	(2.80)
Top 51–500 BA	1.73	4.94**	1.97	4.41	-0.08	1.95	-1.09	1.23
	(1.29)	(2.45)	(1.40)	(2.79)	(0.94)	(1.89)	(1.16)	(2.12)
Top 501–1000 BA	-1.00	-3.41	1.35	0.66	-0.85	-0.81	-1.43	-0.52
	(1.63)	(3.21)	(1.87)	(3.67)	(1.30)	(2.51)	(1.51)	(2.68)
BA not found	-8.85***		-19.03***		-6.16***		-9.93***	
	(1.27)		(1.45)		(0.93)		(1.06)	
Sample	All	BA found	All	BA found	All	BA found	All	BA found
Dep. var mean	8.89	16.64	12.31	23.99	4.28	8.02	7.03	11.99
N	5,928	2,693	5,928	2,693	5,928	2,693	5,928	2,693
Pseudo R^2	0.31	0.24	0.23	0.10	0.25	0.21	0.14	0.11
Note:	*p<0.1; **p<0.05; ***p<0.01							

Notes: Logit average marginal effects $\times$ 100 (percentage points). Delta method standard errors. Controls: university tier dummies, BA-not-found, gender, IMO performance (linear + quadratic), country FE, cohort FE, IMO participations. Compare to Table 3 (LPM).

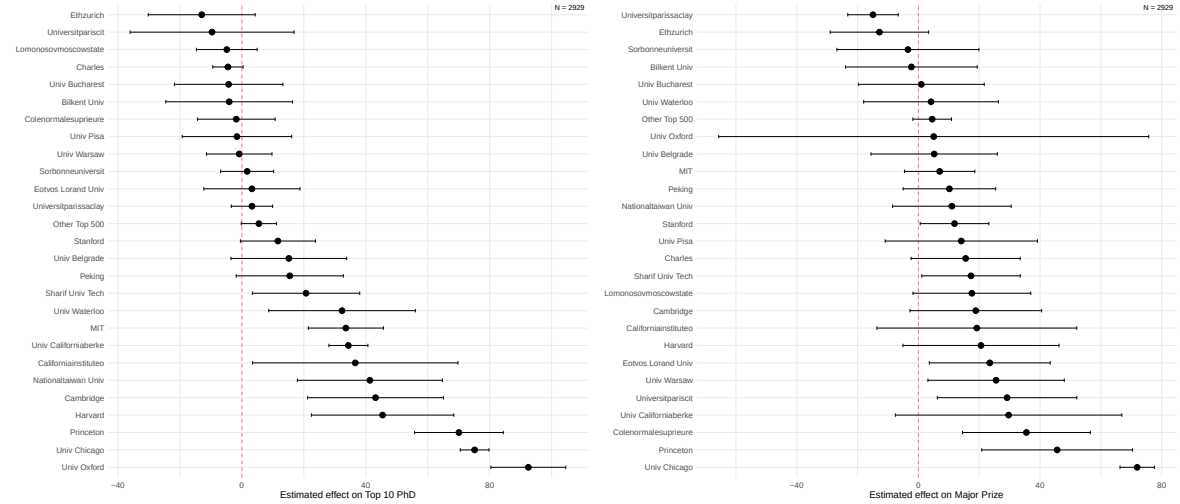
Table A.24: Logit Average Marginal Effects: Field Sorting (Non-US/UK, Last Competition $\leq$ 2005)

	Dependent variable:							
	In Academia	In Academia	In Math	In Math	IT job	IT job	Finance job	Finance job
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top 10 BA	-8.42***	-6.81**	-6.59**	-5.68	-0.85	-0.14	4.99***	10.04***
	(2.88)	(3.11)	(2.66)	(3.95)	(2.58)	(3.93)	(1.53)	(2.65)
Top 11–50 BA	-5.34*	-0.37	-6.16**	-4.12	-2.29	-0.73	2.73	6.48**
	(2.98)	(3.41)	(2.65)	(4.13)	(2.64)	(4.17)	(1.66)	(2.91)
Top 51–500 BA	1.49	4.50*	1.84	4.33	-4.54**	-0.22	-2.40*	0.65
	(2.22)	(2.63)	(1.89)	(3.02)	(1.89)	(3.14)	(1.30)	(2.38)
Top 501–1000 BA	1.55	0.28	-1.87	1.32	-1.17	-1.98	-3.52**	-3.94
	(3.08)	(3.52)	(2.52)	(3.89)	(2.56)	(4.07)	(1.77)	(3.22)
BA not found	-37.59***		-21.70***		-25.20***		-12.81***	
	(1.49)		(1.56)		(1.52)		(1.17)	
Sample	All	BA found	All	BA found	All	BA found	All	BA found
Dep. var mean	47.67	76.05	24.93	40.25	23.95	38.73	8.81	15.26
N	5,928	2,693	5,928	2,693	5,928	2,693	5,928	2,693
Pseudo R^2	0.29	0.14	0.21	0.13	0.17	0.08	0.14	0.09
Note:	*p<0.1; **p<0.05; ***p<0.01							

Notes: Logit average marginal effects $\times$ 100 (percentage points). Delta method standard errors. Controls: university tier dummies, BA-not-found, gender, IMO performance (linear + quadratic), country FE, cohort FE, IMO participations. Compare to Table 6 (LPM).

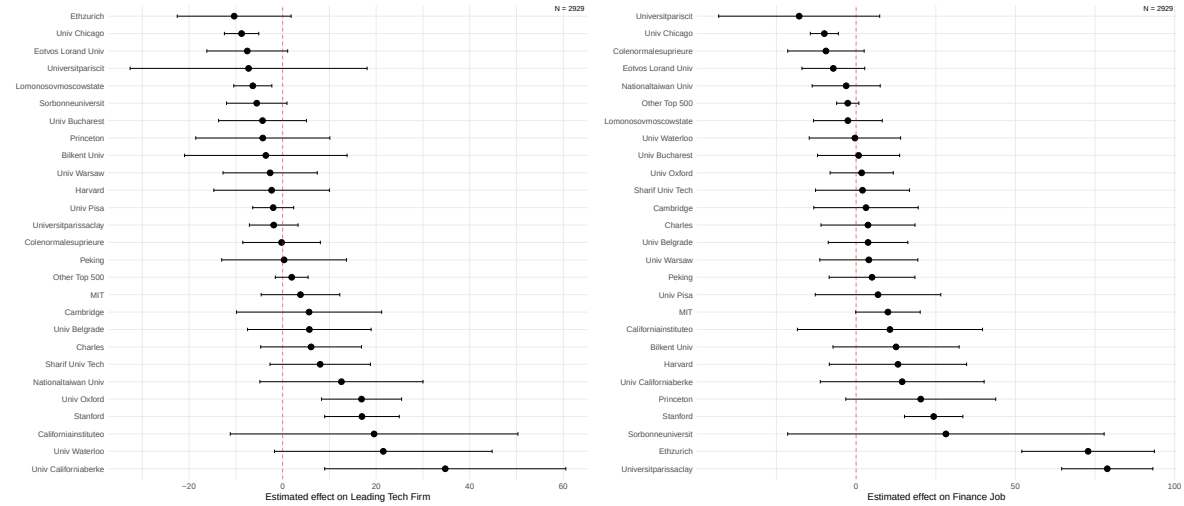
C University-Level Coefficient Plots

Figure A.5: University-Specific Coefficients: Academic Outcomes (Non-US/UK, Medalists Only)



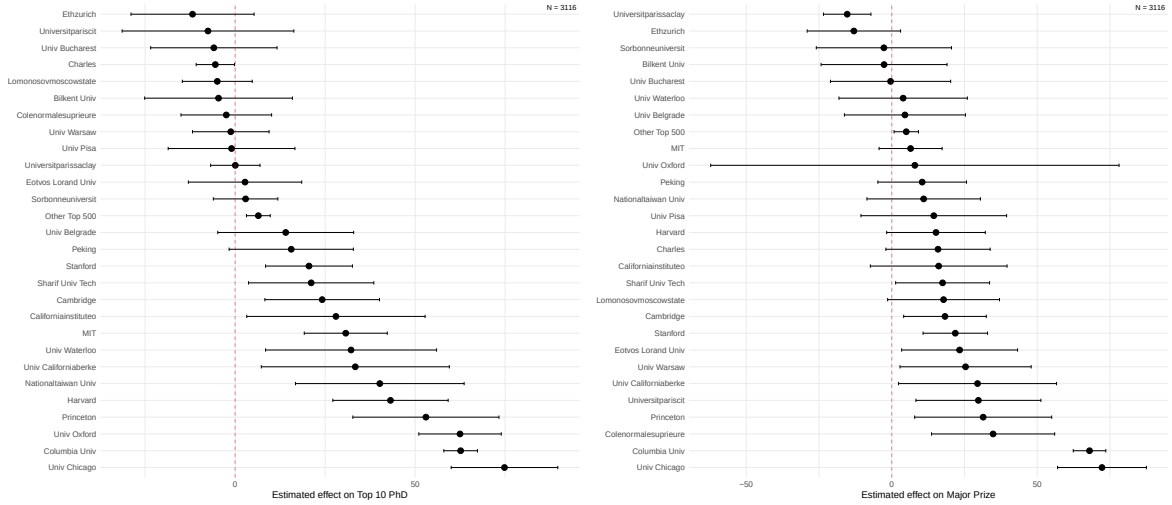
Notes: Coefficient on university-specific indicators (relative to outside top 500), controlling for IMO performance, gender, country FE, year FE, and number of participations. Non-US/UK origin, last competition $\leq$ 2005. 95% CI (HC1).

Figure A.6: University-Specific Coefficients: Industry and Field Outcomes (Non-US/UK, Medalists Only)



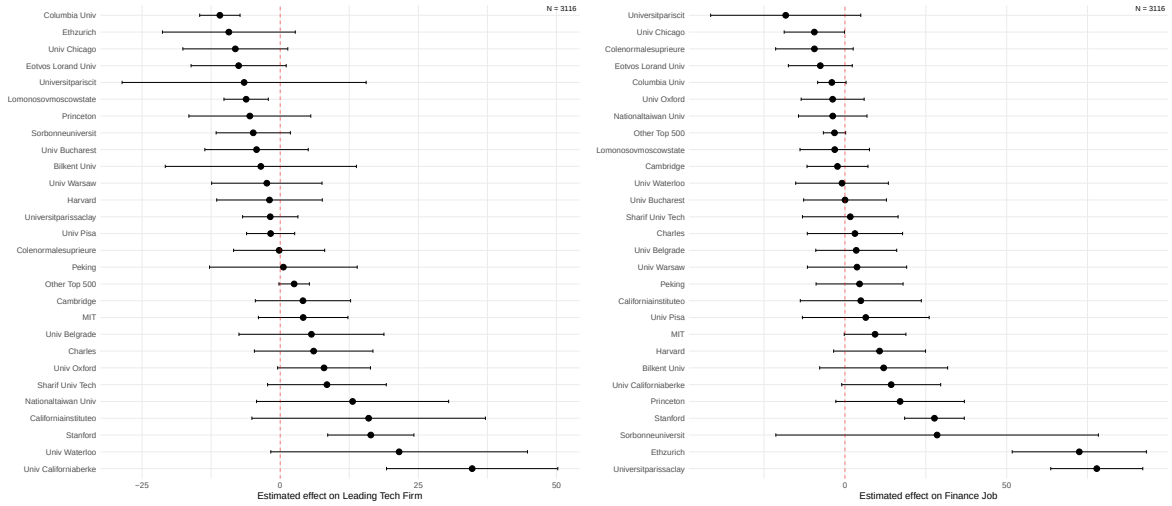
Notes: Coefficient on university-specific indicators (relative to outside top 500), controlling for IMO performance, gender, country FE, year FE, and number of participations. Non-US/UK origin, last competition $\leq$ 2005. 95% CI (HC1).

Figure A.7: University-Specific Coefficients: Academic Outcomes (Including US/UK, Medalists Only)



Notes: As in Figure A.5, but including US and UK origin participants. Coefficient on university-specific indicators (relative to outside top 500), controlling for IMO performance, gender, country FE, year FE, and number of participations. Last competition $\leq$ 2005. 95% CI (HC1).

Figure A.8: University-Specific Coefficients: Industry and Field Outcomes (Including US/UK, Medalists Only)



Notes: As in Figure A.6, but including US and UK origin participants. Coefficient on university-specific indicators (relative to outside top 500), controlling for IMO performance, gender, country FE, year FE, and number of participations. Last competition $\leq$ 2005. 95% CI (HC1).

D Validation of Manual Coding

We validated our university coding against two external administrative sources.

MIT enrollment verification. Using MIT's undergraduate commencement programs (2021–2024), we matched graduate names to 2015–2019 IMO medalists. Our initial manual search had identified 112 medalists as MIT undergraduates; the commencement match revealed 5–8 additional medalists, of whom 5 could be confirmed. In December 2024, MIT's Registrar's Office independently verified the full list of 1,134 2015–2020 medalists against their enrollment records, identifying 9 medalists not in our original manual coding—5 with no previously recorded institution and 4 coded at other universities (likely graduate students in MIT's system). After incorporating LLM and LinkedIn data, our combined coding captures all 5 true undergraduate discoveries, yielding zero missed MIT placements.

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 identifies 111 Cambridge medalists among 2015–2020 participants. We matched all medalists against the yearbooks: among those with a known non-Cambridge institution, 9.5% produced a false match, consistent with the initial validation. Among medalists without any identified institution, we found 10 yearbook matches; after adjusting for the false-match rate, approximately 9 are likely real Cambridge students not yet captured.[12] This yields an inflation ratio of $1.08 = (111 + 9)/111$.

The average inflation ratio across both institutions is $1.04 = (121 + 0 + 111 + 9)/(121 + 111)$. We extrapolate this ratio to other top-10 universities when estimating the full allocation of medalists to university tiers.

E A Simple Framework for Selection vs. Treatment

This appendix formalizes the cross-outcome consistency argument of Section 4.3. The framework clarifies the structural restrictions that pure selection must satisfy to explain the joint pattern of field sorting and prize rates, and shows why the treatment interpretation is more parsimonious.

[12]The initial manual-only validation, which started from 69 identified Cambridge medalists, estimated 14 missed. The LLM and LinkedIn data have since captured most of these, reducing the residual undercount.

E.1 Setup

Consider a population of agents, each with:

- Math ability $a_i \in \mathbb{R}_+$ (observed via IMO score);
- Unobserved type $\theta_i \in \mathbb{R}_+$ (ambition, preparation, family resources—anything that predicts both university placement and career outcomes);
- Migration cost $m_i \geq 0$ (determined by country; $m_i = 0$ for US/UK).

Define the latent admission index

$$S_i = \alpha a_i + \beta \theta_i - m_i + \eta_i, \qquad \alpha, \beta > 0 \tag{3}$$

and assignment rule $T_i = \mathbf{1}[S_i \geq 0]$. Ability and type raise top-10 attendance; migration costs reduce it.

After university, each agent chooses between *academia* (A) and *non-academia* (N). Let the latent utility difference be

$$V_i \equiv U_i^A - U_i^N = \gamma a_i - \lambda \theta_i + \tau T_i + \varepsilon_i \tag{4}$$

where ε_i has CDF G and density $g > 0$. Then

$$p_A(a, \theta, T) \equiv \Pr(d_i = A \mid a_i = a, \theta_i = \theta, T_i = T) = G(\gamma a - \lambda \theta + \tau T),$$

and $p_N(a, \theta, T) = 1 - p_A(a, \theta, T)$. The key assumptions are:

A1. $\gamma > 0$: High math ability creates comparative advantage in academia.

A2. $\lambda \in \mathbb{R}$: The sign of λ determines whether the unobserved type pushes away from academia ($\lambda > 0$) or toward it ($\lambda < 0$). The data discipline this: conditional on ability, top-10 attendees are less likely to work in academia, so any θ that explains both selection into top-10 and the observed field sorting must have $\lambda > 0$.

A3. $\tau \leq 0$: If treatment operates, top universities weakly push toward non-academic careers through exposure to finance, tech, and entrepreneurship. Under the null, $\tau = 0$.

Only those who stay in academia can win academic prizes. Define

$$q(a, \theta, T) \equiv \Pr(\text{prize}_i = 1 \mid d_i = A, a_i = a, \theta_i = \theta, T_i = T), \qquad \frac{\partial q}{\partial a} > 0 \tag{5}$$

and for non-academics, $\Pr(\text{prize}_i = 1 \mid d_i = N, \cdot) = 0$. Hence the overall prize probability conditional on (a, θ, T) is

$$p_P(a,\theta,T) \equiv \Pr(\text{prize}_i = 1 \mid a,\theta,T) = p_A(a,\theta,T)\, q(a,\theta,T). \tag{6}$$

E.2 Pure Selection ($\tau = 0$, $q(a,\theta,T) = q(a,\theta)$)

Under the null, T_i has no direct effect. Conditional on (a_i, m_i), top-10 attendees simply have higher θ_i (from (3)).

Field sorting. Since $p_A(a,\theta) = G(\gamma a - \lambda\theta)$ under the null,

$$\frac{\partial p_A}{\partial \theta} = -\lambda g(\gamma a - \lambda\theta), \qquad \frac{\partial p_N}{\partial \theta} = +\lambda g(\gamma a - \lambda\theta).$$

Therefore, selection can explain "top-10 $\to$ fewer in academia" only if $\lambda > 0$:

$$\frac{\partial p_A}{\partial \theta} < 0, \qquad \frac{\partial p_N}{\partial \theta} > 0.$$

This is a testable restriction, not an assumption. *Selection can explain field sorting only if $\lambda > 0$.*

Prizes. Differentiate (6) with respect to θ:

$$\frac{\partial p_P}{\partial \theta} = \underbrace{\frac{\partial p_A}{\partial \theta}}_{<0 \text{ if } \lambda>0} q + p_A \underbrace{\frac{\partial q}{\partial \theta}}_{\text{intensive margin}} \tag{7}$$

The first term is the extensive-margin loss: higher θ moves people out of academia. The second term is the intensive-margin gain among those who remain in academia.

Proposition 1 (Condition for selection to explain both facts)**.** *Under the null, the joint observation that top-10 attendees are (i) less likely to be in academia and (ii) more likely to win prizes requires*

$$\frac{\partial q/\partial \theta}{q} > \frac{-\partial p_A/\partial \theta}{p_A}.$$

That is, the elasticity of prize productivity with respect to θ must exceed the elasticity of academic exit.

Proof. Set the right-hand side of (7) positive and divide by $p_A \cdot q > 0$. □

In words: for pure selection to match the data, θ must both redirect people away from academia (*extensive loss*) and, at the same time, raise within-academia prize productivity enough

to offset that loss (*intensive gain*). As discussed in Section 4.3, ambition plausibly helps with the intensive term but struggles with the extensive term; wealth and preparation help with selection into top universities but, if anything, predict the wrong field-sorting sign.

Robustness to $\text{Corr}(\theta, a)$**.** Proposition 1 holds for any joint distribution of (θ, a). What depends on $\text{Corr}(\theta, a)$ is the *magnitude* of the selection differential $E[\theta_i \mid T_i = 1, a_i] - E[\theta_i \mid T_i = 0, a_i]$. Positive correlation—the most plausible case, since richer families produce both higher ability and higher θ—reduces residual θ-variation conditional on a, making the selection story *harder* to sustain. The sensitivity analysis (robustness values of 25% for top-10 PhD and 8% for major prizes; Cinelli and Hazlett 2020) addresses the magnitude question directly.

In short, the argument has two layers: *structure* (what θ must do, Proposition 1) and *magnitude* (how large θ must be). The correlation between θ and a affects magnitude only, and the sensitivity analysis already addresses that. If anything, positive correlation tightens the constraint.

E.3 Treatment ($\tau < 0$, $q(a, \theta, 1) > q(a, \theta, 0)$)

Under the alternative, top universities have two independent effects:

1. **Career redirection** ($\tau < 0$): Exposure to finance, tech, and entrepreneurship shifts marginal agents out of academia.

2. **Productivity enhancement** ($q(a, \theta, 1) - q(a, \theta, 0) > 0$): Better mentorship, stronger peers, and institutional resources raise the research output of those who stay in academia.

Because T is binary, use a discrete decomposition. Let $p_A(t) \equiv p_A(a, \theta, t)$ and $q(t) \equiv q(a, \theta, t)$. Then

$$\Delta_T p_P \equiv p_P(a, \theta, 1) - p_P(a, \theta, 0) = \underbrace{\left[p_A(1) - p_A(0)\right] q(0)}_{\text{redirection term}<0} + \underbrace{p_A(1) \left[q(1) - q(0)\right]}_{\text{productivity term}>0}.$$

The treatment model therefore requires only that the productivity term outweigh the redirection term—a quantitative condition, not a structural one.

E.4 Summary

Prediction	Selection	Treatment
Fewer in academia	✓ ($\lambda > 0$)	✓ ($\tau < 0$)
More in finance	✓	✓
More prizes	Requires Prop. 1	Natural
More top PhDs	✓	✓
More AI/startups	✓	✓
Joint pattern	*Restrictive*	*Consistent*

Each outcome individually is consistent with both stories. The distinguishing power comes from the *combination* of field sorting and prizes: selection requires a single θ that simultaneously redirects people away from academia and raises academic productivity, while treatment separates these into independent channels.

E.5 Extensions

Complementarity with ability. The data show that the association between T and prizes increases with a (Section 4.4). Under treatment, this follows if university resources and ability are complements in prize productivity among those who stay in academia ($\partial^2 q/\partial a\,\partial T > 0$): mentorship quality, seminar culture, and peer interactions are more productive when combined with stronger baseline ability. Under selection, a similar pattern requires a and θ to be complements in q—possible but not generic.

US vs. UK. Career redirection should be stronger where the non-academic outside option is richer. The US has deeper finance and tech sectors than the UK, so $|\tau^{US}| > |\tau^{UK}|$. Empirically, US universities predict shifts into finance and AI/entrepreneurship, while UK universities predict comparable academic outcomes but no industry redirection. Under pure selection, it is unclear why θ would generate field sorting in the US but not the UK, since both attract similarly talented students.

E.6 Limitations

This framework clarifies the *structure* of the selection-vs.-treatment argument—what selection would need to look like, and why the observed pattern is more naturally consistent with treatment. It does not prove causality. The model does not rule out a multi-dimensional $\theta = (\theta_1, \theta_2)$ where one component drives field sorting and another drives prize productivity. But this requires

two independent unobservables, each explaining a substantial share of residual variation in both treatment and outcome (Cinelli and Hazlett, 2020), and each correlated with top-10 attendance conditional on IMO performance and country. The two arguments—magnitude (sensitivity analysis) and structure (cross-outcome consistency)—are complementary. Together they set a high bar, but neither individually nor jointly constitutes a proof.

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.