Talent matters: Evidence from Mathematics*

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Abstract

This paper studies how talent translates into knowledge production, and whether this varies for talented people born in different countries. We construct an original dataset covering the career histories and scientific output of the participants to an international competition for high school students - the International Mathematics Olympiad (IMO). This enables us to measure talent in late teenage years in a comparable manner across countries. We first document that performance at the IMO is strongly correlated with production of cutting-edge mathematics in later years. We provide evidence that this correlation reflects the underlying talent distribution rather than a success begets success dynamic. We then show that IMO participants from low- and middle-income countries produce consistently less mathematical knowledge than equally talented participants from high-income countries. Our results suggest that the quantity of lost knowledge production arising from cross-country differences in the productivity of IMO participants is sizeable, and that this lost knowledge production is not easily replaced by other mathematicians.

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1 Introduction

The production of knowledge is often perceived to be the archetype of a cognitively demanding activity that requires some form of innate or natural ability (talent). PhD physicists are reported to have an average IQ in the neighborhood of 140 (Harmon 1961). The top results of a Google search of the term 'genius' are images of Albert Einstein, a scientist. If talent is important in knowledge production, this raises the distinct possibility that the rate of knowledge production may be slowed if highly talented people eschew careers in knowledge production. Yet, there has been little systematic study on the extent to which talented individuals become knowledge producers (or not), and how talent translates into knowledge production more generally.[1]

This paper seeks to contribute filling this gap. We ask two questions in particular. First, how does knowledge produced depends on an individual's talent? Second, conditional on a given level talent, what is the impact of country of birth on knowledge produced? Answering those questions raises three major empirical challenges: (1) measuring talent; (2) measuring talent in a comparable way across multiple countries; and (3) constructing a sample without selecting on eventual success in knowledge production. To address these challenges, we focus on knowledge production in mathematics and use a unique institutional feature of this discipline: the International Mathematics Olympiads (IMO), a prominent competition for high-school students. This setting allows us to measure talent in teenage years (as proxied by IMO scores[2]) as well as to conduct direct comparisons of talent in teenage years across countries. By connecting multiple sources, we are able to build an original database covering the education history and publications of the population of IMO participants participating across 20 years of competition (1981-2000; n=4,711).

[1] A notable exception is Aghion et al. (2018) who find a significant but relatively weak correlation between visiospatial IQ (from an army entrance exam) and the propensity to becoming an inventor in Finland. Bell et al. (2017) also report a correlation between 3rd grade math score and the propensity to become a patent inventor in the U.S. There is also a psychology literature investigating the nexus between intelligence, creativity and scientific achievement. For instance, Cox (1926) estimates IQ scores for 300 'geniuses' who made outstanding achievement to science.

[2] IMO scores are an imperfect measure of talent since they also reflect training undertaken for the IMO and human capital accumulated more generally. However, it is difficult to imagine measures of ability that would not be based on some type of test and hence immune from that criticism. Our proxy has the advantage to be comparable across countries and informative for differences at the top of the talent distribution

We first document a salient positive correlation between the points scored at the IMO and subsequent mathematics knowledge production. Each additional point scored on the IMO (out of a total possible score of 42) is associated with a 2.6 percent increase in mathematics publications and a 4.5 percent increase in mathematics citations. These correlations reflect both the extensive and intensive margins: strong IMO performers are more likely to become professional mathematicians (as proxied by getting a PhD in mathematics); and conditionally on becoming professional mathematicians, they are more productive than lesser IMO performers.

We then investigate whether success at the IMO might have a causal effect on subsequent achievements in mathematics due to a success begets success dynamics. To do so, we exploit the fact that IMO medals are an important summary of IMO performance, and are allocated solely based on the number of points scored at the IMO. We implement a regression discontinuity research design comparing those who nearly made medal threshold versus those who nearly missed them. We find no evidence of a causal effect of medals or better medals on subsequent performance. We thus interpret the medal-math achievement relationship as reflecting underlying differences in talent rather than a success begets success dynamic.

Next, we investigate differences across countries of origin by analyzing the career outcomes and knowledge production of IMO participants controlling for IMO score. We find that there is a developing country penalty throughout the talent distribution in our sample. That is, compared to their counterparts from high-income countries who obtained the same score in the IMOs, participants born in low- or middle-income countries produce considerably less knowledge over their lifetime. A participant from a low-income country produces 35% fewer mathematics publications, and receive over 50% fewer mathematics citations than an equally talented participant from a high-income country. Finally, we investigate whether this developing country penalty may have decreased over time, perhaps reflecting better opportunities for aspiring mathematicians from developing countries. We do find that the developing country penalty has decreased over time, though not at the top of the talent distribution.

Finally, we present three pieces of evidence to assess the broader implications of losing a few talented individuals to mathematics. First, we perform a back of the envelope calculation asking how much more mathematics knowledge could be produced if IMO participants from developing countries produced knowledge at the same rate as those from developed countries. We conclude that the knowledge production (from IMO participants) could be 10% higher in terms of publications and 17% in terms of cites.[3] Second, we show that

[3]This calculation does not take into account countervailing effects on mathematics production by other

strong performers at the IMO have a disproportionate ability to produce frontier mathematical knowledge compared to PhD graduates and even PhD graduates from elite schools. The conditional probability that an IMO gold medalist will become a Fields medalist is two order of magnitudes larger than the corresponding probability for a PhD graduate from a top 10 mathematics program. Third, we show that while developing country participants are slightly more likely to do a PhD in a discipline other than mathematics, this far from offsets the difference observed in getting a mathematics PhD. Thus, the loss to mathematics of losing talented individuals does not appear to be offset by gains in other domains of production.

This works builds upon the macroeconomic literature on talent allocation and the microeconomic literature on the origin of knowledge producers.[4] Baumol (1990) and Murphy, Shleifner & Vishy (1991) emphasize the allocation of talent across different sectors of the economy as being key for economic growth. More recently, Hsieh et al. (2013) attribute part of aggregate wage growth in the U.S. to the integration of talented women and blacks in the U.S. labor market. Most relevant for us, a recent empirical literature investigate how children's socioeconomic and geographic background influence the likelihood of becoming a patent inventor in the U.S. (Bell et al. 2017, Akcigit, Grigsby & Nicholas 2017, Celik 2017) and in Finland (Aghion et al. 2018). A consistent finding is that children of low-income parents are much less likely to become inventors than their higher-income counterparts. Bell et al. (2017) also report considerable differences between states of birth in the likelihood of becoming an inventor - for instance they find that children born in Massachusetts are five times more likely than children born in Alabama to become inventors.

Our results echo these differences at the international level. Besides the cross-country dimension, a distinguishing feature of our data is that we have a sample of individuals in the very right tail of the ability distribution; and we document that even there different background results in substantial differences in knowledge produced. The evidence we present on the importance of talent in the production of frontier knowledge also puts further light on the costs of having talented individuals eschew careers in knowledge production.

More generally, our results also map into the study of the determinants of the rate of knowledge production. The endogeneous growth literature has studied the size of the knowledge production sector (see e.g. Jones 2002, Freeman & Von Reenen 2009, Bloom

mathematicians, nor do we quantify the costs of enabling talented individuals from developing countries to realize their potential in mathematics. See the main text for further discussion.

[4]We also build on the literature on the role of place in knowledge production (Kahn & MacGarvie 2016), and on the determinants of high math achievement (Andreescu et al. 2008, Ellison & Swanson 2010, Ellison & Swanson 2016)

et al. 2017) but has given less attention to its composition. Similarly, the literature on the economics of science has typically focused on how the institutions and incentives affect the productivity of existing researchers rather than who becomes a scientist or knowledge producers in the first place.[5] This study suggests that the selection of talented individuals into knowledge production may be important for the rate of scientific progress.

The paper proceeds as follows. Section 2 describes the International Mathematics Olympiads. Section 3 presents the data. The results on the link between IMO success and long-term achievements are in section 4 and those on cross-country comparisons are in section 5. Section 6 provides additional evidence on the importance of losing a few talented individuals and section 7 concludes.

2 The International Mathematics Olympiads

Since the International Mathematics Olympiad (IMO) plays an important role in our research design, we describe it in some details in this section. The IMO is a competition held annually since 1959. Participants travel to the location of IMO (typically a different city every year) together as part of a national team. Initially, only Eastern European countries sent participants but over time participation expanded to include over 100 countries.[6] The competition is aimed at high school students with the requirements that participants be younger than 20 years of age and not enrolled at a tertiary education institution.

The IMO participants are selected by their national federation (up to six per country), often on the basis of regional and national competitions. Some participants compete several years successively though the majority of participants only compete once. They solve a total of six problems drawn from geometry, number theory, algebra and combinatorics. Each problem is worth 7 points and participants can score up to 42 points. Appendix A provides additional information on IMO problems, including two examples. Medals are awarded based solely on the sum of points collected across problems. Slightly fewer than half of the participants receive medals, which can be either gold, silver or bronze. An "honourable mention" recognizing a perfect solution to one problem has been given out to non-medalists

[5]For instance, Borjas & Doran (2012) study the productivity of U.S. mathematicians following a large influx of Russian mathematicians into the U.S. Other studies on the determinants of scientific productivity among established scientists include Azoulay, Graff-Zivin & Manso (2011), Azoulay, Graff Zivin & Wang (2010), Waldinger (2011), Jacob & Lefgren (2011), Ganguli (2017), Iara, Schwarz & Waldinger (forthcoming). For a more general survey on the economics of science, see Stephan (2012)

[6]The United Kingdom and France joined in 1967, the U.S. joined in 1974 and China in 1985. The only countries with population above 20 millions that never participated are Ethiopia, Sudan and the Democratic Republic of Congo.

since 1987.

Several IMO participants are known to have had outstanding careers as professional mathematicians. Maryam Mirzakhani, an IMO gold medalist with a perfect score, was the first woman to win the Fields medal - the most prestigious award in mathematics. Terence Tao received a gold medal at the 29th IMO and went on to win the Fields medal and is one of the most productive mathematician in the world. Another IMO gold medalist, Gregori Perelman, solved the Poincaré conjecture and famously declined the Fields medal as well as the Millenium Prize and its associated one million dollar purse. Out of the twenty-two Fields medals awarded between 1994 and 2014, twelve went to former IMO medalists (see table 1).

(insert table 1 about here)

3 Data

Multiple sources of data were combined to create the original data for this paper. We started with the official IMO website: http://www.imo-official.org. For each participant, the website lists the name of the participant, the country (s)he represented and the year of participation, the number of points obtained on each problem and the type of medal, if any. We extracted data on all IMO participants from that website and then selected those who participated between 1981 and 2000 included.[7] Some participants compete in multiple years in which case we only kept the last participating year. We ended up with a list of 4,711 individuals.

We then constructed long-term performance outcomes in mathematics for these individuals using PhD and bibliometric data. For PhD theses, we relied on the Mathematics Genealogy Project. The Mathematics Genealogy Project is a volunteer effort whose mission is 'to compile information on all mathematicians in the world'.[8] It has achieved broad coverage, with information on more than 200,000 mathematicians. For each graduating student, it lists the university, the name of the advisor, the year of graduation and the topic of the dissertation. For bibliometric data, we used MathSciNet data which is produced by Mathematical Reviews under the auspices of the American Mathematical Society. While the

[7]We did not include later cohorts of participants as we wanted enough time to have elapsed to construct meaningful long-term outcomes. In principle, we could include earlier cohorts but those are small as relatively few countries were participating in the 1970s.

[8]One might worry that the coverage of the Mathematics Genealogy Project might be worse for developing countries, which would problematic for cross-country comparisons. However, we have encountered only few cases of individuals with math publications (or with a faculty appointment in mathematics) that were not listed in the genealogy project, and these were not necessarily from developing countries.

underlying publication data is richer, our outcomes are based on total publications and cites by author as computed by MathSciNet (and reflecting the manual author disambiguation by the publishers of Mathematical Reviews). Both of these databases have been used in prior research (Borjas & Doran 2012, 2015a, 2015b, Agrawal, Goldfarb & Teodoridis 2016). We complemented the publication data by collecting a list of speakers at the International Mathematics Congresses (IMC) and tagging IMO participants who spoke at the IMC congress. Being invited to speak at the IMC congress is a mark of honor for mathematicians and we use it a measure of community recognition independent of bibliometrics. Similarly, we tag IMO participants who received the Fields medal.

While these measures give us a reasonable overview of an individual's contribution to mathematics, they are silent on what individuals do when they choose a different career paths. To partially shed light on the non-mathematics careers, we manually searched the names of IMO participants online. We use the results of the manual searches to generate two measures: (1) whether the person has a PhD outside mathematics, (2) whether the presence has any kind of 'online presence' - such as a linkedin profile, an online bio, or a personal web page. Given that this part of the data collection is particularly time-intensive, this information was only collected for the IMO medalists (2,273 people out of the 4,711 participants).

Our final database covers the population of IMO participants who obtained a medal between 1981 and 2000 (4,711 people). Besides information on IMO participation (year, country, points scored, type of medal), we know whether the person has a PhD in mathematics, and if so in which year and from which school, mathematics publications and cites counts until 2015 and whether that person was a speaker at the IMC Congress or a Fields Medalists. For the medalists, we also whether that person has a PhD outside mathematics; and whether s(he) has some form of online presence. For the IMO participants who have a PhD in mathematics, we are interested in whether they have a graduated from an elite school; we proxied this by graduating from one of the top ten school in the Shanghai 2010 mathematics rankings (cf table A6 for the list).

Table 2 presents descriptive statistics on our sample. Around 8% of IMO participants earn a gold medal; while 16% have a silver medal and 24% have a bronze medal; a further 10% have an honourable mention (recognizing a perfect solution to one problem). Around 22% of IMO participants have a PhD in mathematics; of those around a third have a PhD in mathematics from a top 10 school. One percent of IMO participants became IMC speakers, and 0.2% became Fields medalists. Collectively, the IMO participants in our sample produced more than 15,000 publications and received more than 160,000 cites. In the subsample of medalists with manually collected information, around 5% have a PhD in a discipline other than mathematics, and slightly more than half have some form of online presence.

(insert table 2 about here)

We proxied country of origin by the country individuals represented at the IMO. Around half of the participants were from high-income countries (as per the 2000 World Bank classification), 23% from upper middle income countries, 16% from lower middle-income countries; and 11% from low-income countries. Historically, the most successful countries at the IMO have been China (54 gold medals in our sample), followed by USSR/Russia (43), the U.S.A. (27) and Romania (26). Germany, Bulgaria, Iran, Vietnam, the U.K., Hungary and France also have more than 10 gold medalists in our sample.

(insert figure 1 and 2 about here)

Finally, we produced an ancillary dataset that has all the PhD graduates (irrespective of IMO participation) listed in the Math Genealogy Project who graduated between 1990 and 2010 (n=89,086). For those, we know the school and year they graduated from, how many math publications and cites they produced (from MathSciNet) and whether they were IMC speakers or Fields Medalists.

4 How much does teenage talent affect long-term performance?

In this section, we investigate whether teenage talent-as proxied by IMO scores-is correlated with long term performance in the field of mathematics. On the one hand, it is natural to expect performance at the IMO to be positively correlated with becoming a professional mathematician, mathematical knowledge production, and outstanding achievements in mathematics. After all, both IMO problems and research in mathematics are two activities that involve problem solving in the field of mathematics. Moreover, there is ample anecdotal evidence of distinguished mathematicians having won IMO medals.

However, the link between IMO score and long-term performance is less obvious than it seems. IMO problem solving and mathematical research are very different types of work. Mathematical research encompasses activities other problem solving - such as conceptualization and hypothesis generation. Moreover, the IMOs problems are quite different from research problems, in that they are known to have a solution and they have to be solved in a very short time frame, without access to the literature or the help of other mathematicians.[9] Even if talent is indeed important for the production of knowledge, IMO scores may not be a good measure of talent. If some measure of luck or extraeneous factors affect IMO scores, this will introduce classical measurement when considering IMO scores as a measure of talent. We also have to allow for the possibility that IMO scores may be correlated with performance in mathematics research even if IMO scores are uninformative about talent. That scenario could occur if IMO performance had a causal effect on performance, a possibility we will investigate in subsection 4.2.

4.1 Link between IMO score and long-term performance

We begin with some graphical evidence: Figure 3 plots the mean achievements of Olympians by the number of points they scored at the IMO, with a linear fit superimposed. Six achievements are considered: obtaining a PhD degree in mathematics, obtaining a PhD in mathematics from a top 10 school, the number of mathematics publications (in logs), the number of mathematics cites (in logs), being a speaker at the International Congress of Mathematicians, and earning a Fields medal.

(insert figure 3 about here)

The graphs in the first two rows of figure 3 all display a clear positive gradient: IMO participants with higher IMO scores are more likely to have a PhD in mathematics or a PhD in mathematics from a top school; and they produce more mathematical knowledge measured in terms of publications or cites. The two graphs in the bottom rows measure exceptional achievements in mathematics. By definition, these are rare outcomes and the graphs are less smooth, but the broad pattern is similar.

We also investigate the relationship between points scored at the IMO and subsequent achievements in a regression format at the individual level. We regress each achievement on points scored at the IMO, cohort fixed effects, and country of origin fixed effects. Specifically we run specifications of this type:

$$Y_{it} = \beta IMOscore_{it} + \delta X_{it} + \epsilon_{it} \qquad (1)$$

[9]Similarities and differences between IMO problems and research problems are often discussed among professional mathematicians. See e.g. Smirnov (2011)

where i indexes IMO participants and t indexes Olympiad years. Y_{it} is one of the six outcomes variables as previously defined, $IMOscore_{it}$ is the number of points scored at the IMO; X_{it} includes cohort (Olympiad year) fixed effects and country of origin fixed effects.

(insert table 3 about here)

The results suggest (see table 3, panel A) that each additional point scored at the IMO (out of a total possible score of 42) is associated with a 1 percent point increase in likelihood of obtaining a Ph.D., a 2.6 percent increase in publications, a 4.5 percent increase in citations, a 0.1 percent point increase in the likelihood of becoming an IMC speaker, and a 0.03 percent point increase in the likelihood of becoming a Fields medalist.[10] Interestingly, the coefficients for the score on more difficult problems is consistently larger than for the score on less difficult problems, though the latter also tends to be significant (see table 3, panel B). Overall, the results of this subsection suggest that there is a close link point scored at the IMO and future achievements.

4.2 Is the result driven by whether high scorers are more likely to do a PhD?

We proceed by analyzing whether long term performance is correlated once we condition on getting a PhD in mathematics. We have documented in the last subsection that higher scorers are more likely to do a PhD in mathematics. Is the link between IMO points and knowledge produced entirely driven by this extensive margin or is there an intensive margin story as well?

To investigate this intensive margin, we restrict the sample to IMO participants who have a PhD in mathematics ($n = 1023$). In table 4 panel A, we regress pubs, cites, becoming an IMC speaker, and receiving the Fields medal on IMO scores, cohort fixed effects and Olympiad fixed effects. The point estimates are positive and significant: an additional IMO point is associated with a 2% increase in publications, 4% increase in cite, a 0.2 percentage point increase in the propensity to become IMC speaker and a 0.07 percentage point in the propensity to become a Fields Medalist. Interestingly, these estimates are hardly lower than those of table 3 panel A.

(insert table 4 about here)

[10] IMO scores alone explain around 8% of the variation in math PhD, publications and citations (not shown on the table).

In table 4 panel B, we run the same regressions but adding graduate school by olympiad year fixed effects. That is, we compare IMO participants who competed in the same Olympiad and did a mathematics PhD in the same school. Even in this very demanding specification, we find a positive correlation between IMO scores and long-term performance. The point estimates are somewhat lower than in panel A for pubs and cites, but similar for becoming an IMC speaker, and receiving the Fields medal.

4.3 Is there a causal effect of medals on long-term performance?

We have so far documented a link between IMO scores and long-term performance. Could this be because scoring a high score at the IMO boosts one's self-confidence in mathematics or facilitate access to better schools? Could IMO scores-by themselves-have a causal effect on long-term performance? If scoring well at the IMO generates a success begets success dynamic, IMO scores could affect long term performance even if talent is not relevant to the production of knowledge.

While we cannot directly test for a causal effect of scores, we can investigate whether IMO *medals* may have a causal effect on performance.[11] At the IMO, medals are awarded based on an explicit cutoff in the IMO score. For example in the year 2000, all participants who scored 30 points and above received a gold medal, those between 21 and 29 received a silver medal, and those between 11 and 20 received a bronze medal. To the extent that medals play a useful rule of summarizing and communicating IMO performance to outsiders - as one might expect given that IMO medals are frequently mentioned on CVs and linkedin profiles, whereas raw IMO scores are not - the causal effect of IMO medals may be informative about the causal effect of IMO performance more generally.

The IMO medal allocation mechanism is a natural setting for a regression discontinuity (RD) design comparing those who just made the medal (or a better medal) versus those who nearly missed it. The assignment variable here is the number of points scored which completely determine what medal a participant gets. Importantly, the number of points scored cannot be precisely manipulated by participants, and in any case the medal thresholds are not known when the participants solve the problems. Moreover, since the thresholds are different each year, these results are likely to be robust to any sharp non-linearities in the function linking IMO score and performance.

We implement a simple regression discontinuity design by estimating linear regressions

[11] Our outcomes are getting a PhD in mathematics and/or mathematical knowledge produced since the data is too sparse to consider exceptional achievement such as getting the Fields Medal

of the following type:

$$\begin{aligned} y_{it} = \alpha + \beta AboveThreshold_{it} + \delta_1(IMOScore_{it} - Threshold_t) \\ +\delta_2 AboveThreshold_{it} * (IMOScore_{it} - Threshold_t) + \lambda Xit + \epsilon_{it} \end{aligned} \quad (2)$$

Where i indexes IMO participants and t indexes Olympiads. y_{it} is either obtaining a PhD in mathematics, obtaining a PhD in mathematics from a top 10 school, mathematics publications in logs or mathematics cites in logs. $AboveThreshold_{it}$ is an indicator variable for being at or above the medal threshold and our variable of interest. We control for linear distance to the cutoff $(IMOScore_{it} - Threshold_t)$, allowing it to be different on each side of the threshold. Additional controls in X_{it} include cohort fixed effects and country of origin fixed effects.

We have three different time-varying thresholds corresponding to the gold, silver and medals. For each threshold, we construct the sample of participants no more than 5 points from the threshold.[12] To maximise power, we then pool these three samples and look at the effect of being above the threshold across the three thresholds.[13]

(insert table 5, figure 4 about here)

The results are presented in Table 5 while figure 4 shows the mean of each outcome by distance to the threshold. The point estimates for the effect of a (better) medal are close to zero and insignificant for all four outcome variables. That is, controlling for score, being awarded a better medal appear to have no additional benefit on becoming a professional mathematician or future knowledge production.

(insert table 6 about here)

We present two complementary pieces of evidence to conclude this subsection. First, receiving an honourable mention - an award for solving one of the six IMO problems perfectly - does not appear to have a causal effect on long-term performance (see appendix for details). Second, there appears to be a positive gradient between points scored and long-term

[12]The results are robust to varying this bandwidth.

[13]That is, our variable of interest is the effect of being above the threshold which itself a weighted average of the effect of being above the gold threshold, being above the silver threshold and being above the bronze threshold. We find qualitatively similar results when running the regressions separately for each sample/threshold.

performance even within medal bins. For instance, in the sample of gold medalists, IMO points scored is positively correlated with each of the four outcomes (table 6 panel A). The same holds for bronze medalists (table 6 panel A) while for silver medalists, the number of points scored is significantly correlated with two of the four outcomes. Taken together, these results suggest that the link between IMO scores and long-term performance reflect difference in the underlying talent of medalists rather than a causal effect of medals.

5 Does the link between talent and performance depend on your country of origin?

5.1 Link between IMO score and long-term performance by country income group

The previous section establishes that performance at the IMOs is strongly correlated with getting a PhD in mathematics and mathematics knowledge produced. We now proceed to this link vary according to the country of origin of IMO participants. Because we have relatively few participants for any country, we group countries in income groups (according to the 2000 World Bank classification) as a broad proxy of differences of opportunities and environment across countries. We will consider specifically how IMO participants from low- and middle-income countries - about half of our sample - perform in the long run compared to observationally equivalent participants from high-income countries.[14] While our regressions will explicitly control for IMO scores, it is worth noting that participants from developing countries do not score worse at the IMO than those of developed countries.[15]

(insert figure 6 about here)

We begin by exploring graphically the link between points scored at the IMO and the propensity to a PhD in mathematics for participants from different group of countries. In figure 6, we plot the share of IMO participants obtaining a PhD in math by points scored at the IMO (five-points bands) across group of countries. The general pattern we observe is that for a given number of points, the share getting a PhD in math is typically highest for high-income countries, followed by upper middle-income, then by lower middle income, with low-income countries having the lowest share.

[14] We adopt the income group classification of the World Bank (as of 2000).
[15] Cf appendix table A2 for details.

We investigate cross-country differences more formally using the following specification:

$$Y_{it} = \beta_1 IMOscore_{it} + \beta_2 CountryIncomeGroup_i + \eta_t + \epsilon_{it} \tag{3}$$

where as i indexes medalists and t indexes Olympiad years. Y_{it} is an indicator variable for getting a PhD in mathematics, getting a PhD in mathematics from a top school, the publications in logs and the cites in logs. Our variable of interest is the income group of the country that a participant represented at the Olympiad. We include indicator variables for low-income, lower middle-income and upper middle-income with high-income being the omitted category. Crucially, we control for the number of points scored at the IMO, our proxy for talent. We also control for Olympiad year fixed effects (η_t).

(insert table 7 about here)

Results (see table 7) suggest that across all long-term productivity outcome variables IMO participants from low- and middle-income countries significantly underperform compared to their high-income counterparts. For instance, IMO participants from low-income countries are 16 percentage points less likely to do a PhD and 3.4 percentage points less likely to do a PhD in a top school; they produce 35% fewer publications and 57% fewer cites. To put things in perspective, the low-income penalty in getting a math PhD is equivalent to that of scoring 15 fewer points at the IMO. A similar, though less pronounced, pattern can be observed for participants from middle-income countries. We find similar results if we replace country income groups by linear income per capita (cf table A3) or indicator variables for deciles in the income per capita distribution (cf table A4). Naturally, other country characteristics besides income may influence the career choices and knowledge production of IMO participants. In appendix table A5, we show that the number of mathematical articles produced by the origin country is correlated with the publications and cites of IMO participants, though not with the propensity to do a PhD. If we interact the number of points score with the country income group (cf table 8), we find that the low income penalty is larger for individuals who score more points.

(insert table 8 about here)

We also consider whether there is a difference in the mathematics knowledge produced by developing country and developed country IMO participants considering only those who have a PhD in mathematics (table 9). The point estimates for low-income, lower middle income and upper middle income, albeit negative, are not significant. When we compare participants who competed in the same year and went to the same graduate school (IMO participation year by graduate school fixed effects, panel B), the point estimates are positive and significant (with the exception of upper middle-income in the cites regression). Taken together, this evidence suggests that the effect of coming from a developing country may possibly operate primarily through the extensive margin (getting a math PhD) rather than through an intensive one (productivity conditional on having a math PhD).[16]

(insert table 9 about here)

5.2 Is the importance of country of origin decreasing over time?

We now explore whether the low- and middle-income country penalty has changed over time. We repeat the last specifications but now including an interaction term between the country income group and an indicator variable for 'late' cohorts (IMO participants who competed between 1991 and 2000, with those who competed between 1981 and 1990 the omitted category). Results are displayed in table 10.

(insert table 7 about here)

The results are somewhat mixed. On the one hand, the interaction between late and low-income is positive (and significant for three out of the four outcomes), indicating that the penalty associated with coming from a low-income country has decreased over time. However the interaction term between late and upper middle-income is negative; suggesting an increasing gap over time between upper middle-income and high-income countries.

(insert figure 7 about here)

Finally, we present some graphical evidence on how the low-income penalty has evolved over time for different parts of the talent distribution. In figure 7, we plot the difference in the share of medalists getting a PhD in math between high- and low-income countries. We plot this difference separately by five-years bands (of IMO participation) and type of medal. Consistent with the regression results, the difference is always positive. For bronze medalists and silver medalists, the difference has considerably diminished over time. However, for gold medalists we observe no such decrease.

[16] Although we control for the IMO score, this comparison is complicated by the fact that the selection into doing a PhD in mathematics is different for developing country and developed country participants.

Overall, the evidence suggests that coming from a low-income country is less detrimental than it used to be for becoming a professional mathematician and producing mathematical knowledge. However, the gap between high- and low-income countries at the top of the talent distribution has not narrowed.

6 Does losing a few talented individuals matter?

6.1 Quantifying the size of the lost knowledge production

The previous section documented that IMO participants from low- and middle-income countries produce consistently less knowledge that equally talented participants from high-income countries. We now proceed to quantify the size of the knowledge production lost. Specifically, we ask how much knowledge production (from IMO participants) there could be if IMO participants from low-income countries were producing knowledge at the same rate as those from high-income countries. The size of the loss depends on the share of participants in each income groups and the penalty for that group. Around half of the IMO participants and medalists are from low- and middle-income countries (cf descriptive statistics table 2). We multiply the coefficients on the country income groups in our main specifications by the share of IMO participants in each group; and then aggregate across the country income groups (cf table 11). We conclude that the knowledge production (from IMO participants) could be 10% higher in terms of publications and 17% in terms of cites if IMO participants from low-income countries were producing knowledge at the same rate as IMO participants from high-income countries.

(insert table 11 about here)

While this calculation suggests that the benefits of enabling developing country individuals to produce knowledge at the same rate as those from developed countries may be sizeable, we are unable to quantify the costs of doing so, and such costs may be substantial as well.[17] Moreover, enabling developing country individuals to produce more knowledge could reduce the knowledge produced by individuals from developed countries (for instance if the number of important mathematical problems to be solved is fixed, or if native mathematicians in developed countries are crowded out from research positions (Borjas & Doran 2012)).

[17] On the one hand, a number of targeted fellowships for particularly talented individuals, or spots in highly ranked mathematical programs would not be particularly expensive. On the other hands, improving mathematical training and research in developing countries could involve larger costs.

We also need to contend with the possibility that inducing individuals to engage in mathematical careers may reduce distinctive contributions that they may otherwise make outside mathematics. The next two subsections seek to partially address these last two points.

6.2 Comparing IMO participants with other Mathematicians

We have shown that a set of particularly talented individuals from developing countries (the IMO participants and in particular the IMO medalists) produce less mathematical knowledge than a similar set of individuals from developed countries. However, perhaps that knowledge can be replaced by other individuals. This could occur if factors such as effort, luck and/or training could substitute for talent in the production of knowledge. It could also be that there are enough very talented individuals overall that losing a fraction of those is inconsequential for the overall rate of knowledge productions.

A first insight into these issues might be gained from the fact that more than half of the Fields medalists were IMO medalists, as mentioned previously (cf table 1), and all but one of these were gold medalists. We take this fact as evidence that talent is very important for the production of the most groundbreaking mathematical discoveries, as more than half of the Fields medalists had displayed elite problem solving ability (as measured by having an IMO gold medal) when teenagers. Moreover, this is likely to be an underestimate as other Fields medalists might have had high talent/innate ability in a way we do not measure. We also take it as evidence that there are not many individuals that are as talented as the IMO gold medalists.[18]

In order to study these issues in a more systematic manner, we compare IMO medalists with other mathematicians. For this comparison, we constructed a sample with all PhD students obtaining a PhD in mathematics between 1990 and 2010 (n=89,068). We also constructed the subsample of PhD students graduating from top 10 schools (n=9,049). We then constructed the sample of IMOs bronze and silver medalists with a mathematics PhD (n=520) and that of gold medalists with a mathematics PhD (n=145). We then plot (see figure 8) the average number of papers, the average number of citations, the share becoming IMC speakers and the share becoming Fields medalists across the four groups.

[18]An alternative explanation is that the Fields medal committee is somehow biased towards those that were ‘anointed’ as top talent by the IMO gold medal. We cannot completely rule out this explanation, although we have shown earlier that IMO medals do not appear to have a causal effect on the likelihood of getting a mathematics PhD, a mathematics PhD from a top school, or mathematics publications and cites. Another consideration is that both the IMO medalists and Fields medalists disfavour late bloomers as IMO participants must be younger than twenty and Fields medalists younger than 40.

(insert figure 8 about here)

For each outcome, we observe the same pattern: the medalists (and especially the gold medalists) outperform both the other PhD graduates and the PhD graduates from top schools. While the IMO medalists produce more papers and receive more cites than other graduates, we observe a much larger difference for exceptional achievements such as being invited to the IMC Congress and receiving the Fields medal. One interpretation is that talent may be more important for exceptional research achievement rather than more routine knowledge production.

We proceed by comparing IMO medalists to other PhD graduates using regressions. Using the sample of 89,068 mathematics PhD graduates, we regress each of the four outcomes on an indicator variable taking value one for IMO bronze or silver medalists; and an indicator variable taking value one for IMO gold medalists. We run these regressions without other controls in Panel A and include PhD graduation year fixed effects and PhD graduate school fixed effects in column B.

(insert table 12 about here)

We find positive and significant coefficients for both bronze/silver medalists and for gold medalists. The magnitude of the effect is sizeable in the regressions with papers and citations as outcome. But it is considerably larger still for the regressions with exceptional achievements: for the propensity to become IMC speaker, the coefficient for IMO gold medalist is an order of magnitude larger than the mean propensity to become IMC speaker; for the propensity to become a Fields medalist, it is two orders of magnitude larger than the mean propensity to become a Fields medalist. Interestingly, the coefficients are roughly similar when we control for PhD graduate school fixed effects. Overall, we find that IMO medalists who get a PhD tend to outperform both other mathematics PhD graduates and their classmates from the same school.

(insert figure 9 about here)

Finally, we take a brief look at how IMO medalists sort themselves across graduate schools. To do this, we compute the number of IMO medalists graduating with a PhD degree from each school, and plot that against the rank of the school as proxied by the Shanghai university ranking for mathematics (see figure 9). The medalists tend to cluster in the very best schools, with 36% of the IMO medalists who get a PhD in math graduating from the top 10 schools. We see this as further evidence that highly talented individuals (as proxied by IMO medals) are scarce.

6.3 Careers of IMO participants outside mathematics

The last two subsections suggested that the quantity of lost knowledge production arising from cross-country differences in the productivity of IMO participants is sizeable, and that this lost knowledge production is not easily replaceable by that of other mathematicians. These do not necessarily imply that the resulting allocation of talent is inefficient. The efficient allocation of talent would clearly depend (among other considerations) on how valuable mathematical knowledge is to society compared to other goods and services as well the comparative advantage of IMO participants in the production of mathematical knowledge.

In their influential paper on talent allocation and growth, Murphy, Shleifer & Vishny (1991) make a distinction between people who have a strong natural comparative advantage in one activity versus those can become the best in many occupations. We think of IMO participants as being more in the first category given the high specificity of mathematics as a discipline and occupation. Still, our views on whether it is efficient that individuals from developing countries with a talent for mathematics eschew careers in this discipline may be influenced by what else they are doing. Measuring the non-mathematical activities of the IMO participants is intrinsically challenging but for the subsample of IMO medalists, we are able to observe those who have a PhD in a non-mathematics discipline as well as those who have a linkedin profile or some other sort of online presence (without having a mathematics PhD). We regress these two variables on the country income group indicator variables, points scored and cohort dummies (cf table 13 for the results). While developing country participants are slightly more likely to do a PhD in a discipline other than mathematics, this far from offsets the difference observed in getting a mathematics PhD. As far as having a visible online presence without having a mathematics PhD, we see no difference across the country income groups.

(insert figure 13 about here)

7 Conclusion

This paper studied how talent translates into knowledge production, and whether this varies for talented people born in different countries. We investigated that in the context of mathematics knowledge and relied on the scores at the International Mathematics Olympiad (IMO) as a measure of talent in late teenage years that is comparable across countries. We documented a strong and consistent link between IMO scores and a number of achievements in mathematics, including getting a PhD in mathematics, mathematics publications and cites, and getting the Fields medal. We suggested, and provided some evidence, that this correlation reflects the underlying talent distribution rather than a success begets success dynamic. We then showed that IMO participants from low- and middle-income countries produce consistently less mathematical knowledge than equally talented participants from high-income countries. Our results suggest that the quantity of lost knowledge production arising from cross-country differences in the productivity of IMO participants is sizeable, and that this lost knowledge production is not easily replaceable by that of other mathematicians.

While we have devoted considerable attention to the link between IMO score and future performance in mathematics, we are in no way implying that a high ability in problem solving in late teenage years - much less IMO participation or performance - is a necessary condition to become a successful mathematician. Some individuals may excel at mathematics knowledge production without scoring well on IMO-style tests or having a taste for that type of competition. Others may become interested in mathematics after their teenage years. We are using IMO medals as a tool to observe part of the extreme right tail of the ability distribution. What we are suggesting is that it may be a loss to mathematics if individuals who are in the extreme right tail of ability (some of whom are IMO participants and some of whom are not) drop out of mathematics.

One might question whether having less mathematical knowledge produced is in any way bad for welfare. An in-depth analysis or even discussion of the contributions of mathematics to the economy is beyond the scope of this paper. However, we note that there is plenty of anecdotal evidence of mathematical discoveries having direct or indirect practical applications, such as in weather simulations, cryptography or telecommunications.[19,20]

Even if mathematical knowledge production contributes to welfare, the lost knowledge production arising from the under-utilization of developing-country talent is more palatable (or perhaps even desirable) if talent from developing countries is used to produce other types of knowledge. We have shown that while developing country IMO participants are slightly more likely to do a PhD in a discipline other than mathematics, this far from offsets the difference observed in getting a mathematics PhD. We cannot rule the possibility that developing country talent end up in valuable occupations (outside mathematical and non-mathematical knowledge production) where they might make distinctive contributions.

[19]The following quote from Laurent Schwartz presents the indirect benefits of mathematics thus: "What is mathematics helpful for? Mathematics is helpful for physics. Physics helps us make fridges. Fridges are made to contain spiny lobsters...."

[20]A Deloitte report quantified the benefits of mathematical research to the UK economy as above 200 billion pounds (Deloitte, 2012).

However, if we think of IMO participants as having a strong natural comparative advantage in one very particular activity (mathematics) - as we do - this makes it more likely that the current allocation is inefficient.

Having more developing country talent engaged into mathematics production might have side effects on the production of developed country mathematicians. On the one hand, there might be learning and spillovers (Azoulay et al. 2010). On the other hand, competition from developing country talent might induce displacement and crowding out of developed country mathematicians if there is a limited number of spots in graduate school or faculty ranks. Borjas & Doran (2012) document such effects among American mathematicians following the influx of talent Russian mathematicians after the collapse of the Soviet Union. These effects may be important for the distribution of welfare among knowledge producers (and potential knowledge producers). From the perspective of generating knowledge, however, it is highly desirable to have the most talented people engaged in knowledge production: as we show in this paper, they have a disproportionate ability to make ground-breaking contributions.

This paper falls short of identifying why developing country participants eschew careers in mathematics and produce less mathematical knowledge. On the one hand, participants from developing countries might have fewer opportunities in general. They may not have access to excellent training opportunities at home or face higher barriers when applying to universities outside their home countries. On the other hand, they may have different preferences for different types of careers, in particular if career outside mathematics pay more. Future research might shed light on which factors play a larger role in these differences. For now, now we briefly mention several types of supply-side policies that could be useful in this context. First, fellowships for high-end talent to study mathematics at undergraduate and/or graduate level may alleviate resources constraints and make mathematics careers more attractive. Second, top schools could encourage applications from developing countries; recruiting elite talent to their student programs is probably in their interest. Third, strengthening mathematics research and training capacity in developing countries would not only improve the training of those who prefer to stay in their home country but would also make mathematics research careers more attractive to them. While this paper has focused on mathematics, there are other disciplines - such as biomedicine or computer science - where knowledge production is perhaps more important to welfare. We suspect that developing country talent might also be under-utilized in those fields, though it is less clear whether talent is as important in those fields as it appears to be in mathematics.

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Tables

Table 1: IMO Medalists and Fields medalists

Year	Fields medalists by award year (Former IMO medalists in bold)			
1994	Jean Bourgain	**Pierre-Louis Lions**	**J-C Yoccoz**	Efim Zelmanov
1998	**Richard Borcherds**	**Timothy Gowers**	Maxim Kontsevich	Curtis McMullen
2002	**Laurent Lafforgue**	Vladimir Voevodsky		
2006	Andrei Okounkov	**Grigori Perelman**	**Terence Tao**	Wendelin Werner
2010	**Elon Lindenstrauss**	**Ngo Bao Chau**	**Stanislav Smirnov**	Cedric Vilani
2014	**Artur Avila**	Manjul Bhargava	Martin Hairer	**M Mirzakhani**

Notes: Fields medals are a highly prestigious prize awarded every four years to up to four mathematicians under the age of 40.

Table 2: Summary statistics on IMO participants (1981-2000)

Variable	Obs	Mean	Std. Dev.	Min	Max
IMO Score	4,711	16.0	11.3	0	42
Gold Medal	4,711	0.08	0.27	0	1
Silver Medal	4,711	0.16	0.16	0	1
Bronze Medal	4,711	0.24	0.24	0	1
Honourable Mention	4,711	0.10	0.30	0	1
Olympiad Year	4,711	1992.4	5.5	1981	2000
Math PhD	4,711	0.22	0.41	0	1
Math PhD (top 10)	4,711	0.07	0.25	0	1
Pubs	4,711	3.2	11.5	0	264
Cites	4,711	34.5	221.1	0	11,062
IMC speaker	4,711	0.01	0.09	0	1
Fields medalist	4,711	0.002	0.04	0	1
Non-math PhD (*)	2,273	0.05	0.21	0	1
Any web presence (*)	2,273	0.53	0.50	0	1
High-income country	4,711	0.50	0.50	0	1
Upper middle-income country	4,711	0.23	0.42	0	1
Lower middle-income country	4,711	0.16	0.37	0	1
Low-income country	4,711	0.11	0.31	0	1

Notes: The table display descriptive statistics on the sample of all individuals who participated in any IMO from 1981 to 2000. IMO medals are based on the number of points scored (IMO score). Multiple gold, silver and bronze medals are awarded at every IMO. Math PhD is based on the Mathematics Genealogy Project. Math PhD (top 10) is based on the list of the 10 top schools listed in appendix table A6. Pubs and cites are from MathSciNet. IMC speaker stands for speaker at the International Mathematics Congress. Non-math PhD and any web presence were (manually) collected only for the subsample of IMO medalists (2,273 people), hence the lower number of observations. Country income groups are based on the World Bank classification of 2000.

Table 3: IMO scores and subsequent achievements

Panel A	(1) Math PhD	(2) Math PhD (top 10)	(3) Pubs (log)	(4) Cites (log)	(5) IMC speaker	(6) Field medalist
IMO Score	0.0100***	0.0053***	0.0258***	0.0430***	0.0012***	0.0003***
	(0.0008)	(0.0006)	(0.0021)	(0.0035)	(0.0003)	(0.0001)
Olympiad Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4711	4711	4711	4711	4711	4711
Adjusted R2	0.1482	0.1102	0.1402	0.1466	0.0202	0.0012

Panel B	(1) Math PhD	(2) Math PhD (top 10)	(3) Pubs (log)	(4) Cites (log)	(5) IMC speaker	(6) Field medalist
Score on less difficult problems	0.0086***	0.0043***	0.0341***	0.0205***	0.0010***	0.0002
	(0.0011)	(0.0007)	(0.0044)	(0.0027)	(0.0003)	(0.0001)
Score on more difficult problems	0.0126***	0.0075***	0.0611***	0.0371***	0.0019***	0.0007**
	(0.0022)	(0.0015)	(0.0095)	(0.0059)	(0.0006)	(0.0003)
Olympiad Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4492	4492	4492	4492	4492	4492
Adjusted R2	0.1475	0.1119	0.1495	0.1429	0.0249	0.0041

Notes: These regressions are run on the sample of all IMO participants who competed at any point between 1981 and 2000. The dependent variables are as follows: obtaining a math PhD (column 1), obtaining a math PhD from a top 10 school (column 2), the log plus one of mathematics publications (column 3), the log plus one of mathematics cites (column 4), becoming an IMC speaker at the IMC Congress (column 5), becoming a Fields medalist (column 6). The variable of interest in panel A is the number of points scored controlling for cohort (olympiad year) fixed effects and country fixed effects. Panel B distinguishes between the number of points scored normally considered easier (1, 2, 4 and 5) and those considered more difficult (3 and 6); we do not have the score breakdown for all IMOs, hence the lower number of observations in panel B. All regression are estimated by OLS. Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Performance conditional on PhD

Panel A	(1) Pubs (log)	(2) Cites (log)	(3) IMC speaker	(4) Fields medalist
IMO Score	0.0232***	0.0394***	0.0027***	0.0007**
	(0.0055)	(0.0087)	(0.0009)	(0.0003)
Country FE	Yes	Yes	Yes	Yes
Olympiad Year FE	Yes	Yes	Yes	Yes
Observations	1,023	1,023	1,023	1,023

Panel B	(1) Pubs (log)	(2) Cites (log)	(3) IMC speaker	(4) Fields medalist
IMO Score	0.0165*	0.0272**	0.0025**	0.0008
	(0.0088)	(0.0137)	(0.0012)	(0.0005)
Country FE	Yes	Yes	Yes	Yes
Graduate School by Olympiad Year FE	Yes	Yes	Yes	Yes
Observations	1,023	1,023	1,023	1,023

Notes: These regression are on the subset of IMO participants who have a PhD in mathematics (n=1,023). The dependent variables are: the log plus one of mathematics publications (column 1), the log plus one of mathematics cites (column 2), becoming an IMC speaker at the IMC Congress (column 3), becoming a Fields medalist (column 4). The variable of interest in is the number of points scored controlling for cohort (olympiad year) fixed effects and country fixed effects. Panel B also include graduate school by olympiad year fixed effects - comparing participants who participated in the same year and went to the same school for their PhD. All regressions are estimated by OLS. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Regression discontinuity estimates of the effect of (better) medals

	(1) Math PhD	(2) Math PhD (top 10)	(3) Pubs (log)	(4) Cites (log)
Above (better) medal threshold	-0.0078	0.0108	-0.0120	-0.0227
	(0.0307)	(0.0196)	(0.0792)	(0.1300)
Distance from threshold	0.0130*	0.0032	0.0191	0.0253
	(0.0074)	(0.0047)	(0.0192)	(0.0316)
Distance from threshold X above threshold	-0.0071	0.0006	0.0004	0.0166
	(0.0098)	(0.0063)	(0.0255)	(0.0418)
Country FE	Yes	Yes	Yes	Yes
Olympiad Year FE	Yes	Yes	Yes	Yes
Observations	3,347	3,347	3,347	3,347
Mean of dep. var.	0.2844	0.0908	0.5774	0.9586

Notes: The IMO medals (gold, silver and bronze) are allocated solely based on the number of points scored at the IMO. The medal thresholds for a gold, silver, or bronze medal vary from year to year. For each medal threshold, we construct the sample of participants no more than 5 points from the threshold. We then stack these three samples and construct a unique distance (number of points) to the threshold for a (better) medal. The effect of being above the threshold is thus a weighted average of the effect of being above the gold threshold, being above the silver threshold and being above the bronze threshold. The dependent variables are as follows: obtaining a math PhD (column 1), obtaining a math PhD from a top 10 school (column 2), the log plus one of mathematics publications (column 3), the log plus one of mathematics cites (column 4). All regressions are estimated by OLS and include country fixed effect and cohort (olympiad year) fixed effects. Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: IMO score gradient within medal bins

Panel A

	Sample: IMO Gold Medalists			
	(1) Math PhD	(2) Math PhD (top 10)	(3) Pubs (log)	(4) Cites (log)
IMO Score	0.0300***	0.0175**	0.0816***	0.1274***
	(0.0102)	(0.0079)	(0.0280)	(0.0462)
Country FE	Yes	Yes	Yes	Yes
Cohort (Olympiad Year) FE	Yes	Yes	Yes	Yes
Observations	371	371	371	371
Adjusted R2	0.0698	0.1524	0.1393	0.1337

Panel B

	Sample: IMO Silver Medalists			
	(1) Math PhD	(2) Math PhD (top 10)	(3) Pubs (log)	(4) Cites (log)
IMO Score	0.0026	-0.0010	0.0325*	0.0539*
	(0.0066)	(0.0049)	(0.0185)	(0.0300)
Country FE	Yes	Yes	Yes	Yes
Cohort (Olympiad Year) FE	Yes	Yes	Yes	Yes
Observations	775	775	775	775
Adjusted R2	0.1127	0.1304	0.1219	0.1424

Panel C

	Sample: IMO Bronze Medalists			
	(1) Math PhD	(2) Math PhD (top 10)	(3) Pubs (log)	(4) Cites (log)
IMO Score	0.0104**	0.0052*	0.0286**	0.0495**
	(0.0049)	(0.0027)	(0.0132)	(0.0211)
Country FE	Yes	Yes	Yes	Yes
Cohort (Olympiad Year) FE	Yes	Yes	Yes	Yes
Observations	1,127	1,127	1,127	1,127
Adjusted R2	0.0595	0.0642	0.0536	0.0568

Notes: These regressions repeat those of table 3 separately on the subsample of gold medalists (column A), silver medalists (panel B) and bronze medalists (panel C). The dependent variables are as follows: obtaining a math PhD (column 1), obtaining a math PhD from a top 10 school (column 2), the log plus one of mathematics publications (column 3), the log plus one of mathematics cites (column 4). All regressions are estimated by OLS and include country fixed effect and cohort (olympiad year) fixed effects. Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Link between IMO score and long-term performance by country income group

	(1) Math PhD	(2) Math PhD (top 10)	(3) Pubs (log)	(4) Cites (log)
Income group of origin country:				
Low-income	-0.162***	-0.034***	-0.345***	-0.571***
	(0.019)	(0.012)	(0.048)	(0.079)
Lower middle-income	-0.102***	-0.021**	-0.197***	-0.325***
	(0.015)	(0.009)	(0.036)	(0.060)
Upper middle-income	-0.039**	-0.024**	-0.082**	-0.170***
	(0.016)	(0.010)	(0.040)	(0.066)
High-income: omitted category				
IMO Score	0.011***	0.005***	0.027***	0.045***
	(0.001)	(0.000)	(0.001)	(0.002)
Cohort (Olympiad Year) FE	Yes	Yes	Yes	Yes
Observations	4,711	4,711	4,711	4,711
Mean of D.V.	0.217	0.068	0.429	0.710

Notes: We are interested in how becoming a professional mathematician, and the mathematics knowledge produced, depends on income level of a participant's origin country (with the income level based on the World Bank 2000 classification). The omitted country level category is high income country. The dependent variables are as follows: obtaining a math PhD (column 1), obtaining a math PhD from a top 10 school (column 2), the log plus one of mathematics publications (column 3), the log plus one of mathematics cites (column 4). All regressions are estimated by OLS, control for the number of points scored at the IMO and include cohort (olympiad year) fixed effects. Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Link between IMO score and long-term performance by country income group

	(1) Math PhD	(2) Math PhD (top 10)	(3) Pubs (log)	(4) Cites (log)
Income group of origin country:				
Low-income	-0.093***	-0.026	-0.077	-0.103
	(0.033)	(0.021)	(0.084)	(0.137)
Lower middle-income	-0.084***	-0.016	-0.107*	-0.162
	(0.025)	(0.016)	(0.062)	(0.102)
Upper middle-income	-0.048*	-0.001	-0.066	-0.099
	(0.028)	(0.018)	(0.070)	(0.115)
IMO Score	0.012***	0.006***	0.031***	0.052***
	(0.001)	(0.000)	(0.002)	(0.003)
Low-income X IMO Score	-0.004**	-0.000	-0.015***	-0.027***
	(0.002)	(0.001)	(0.004)	(0.006)
Lower middle-income X IMO Score	-0.001	-0.000	-0.006*	-0.010**
	(0.001)	(0.001)	(0.003)	(0.005)
Upper middle-income X IMO Score	0.001	-0.002	-0.001	-0.004
	(0.001)	(0.001)	(0.004)	(0.006)
Cohort (Olympiad Year) FE	Yes	Yes	Yes	Yes
Observations	4,711	4,711	4,711	4,711
Mean of D.V.	0.217	0.068	0.429	0.710

Notes: These regressions repeat those of table 7 but include interactions between the country income group and the number of points scored at the IMO. Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Cross-country comparisons conditional on math PhD

Panel A	(1) Pubs (log)	(2) Cites (log)
Income group of origin country:		
Low-income	-0.203	-0.324
	(0.177)	(0.285)
Lower middle-income	-0.054	-0.074
	(0.115)	(0.186)
Upper middle-income	-0.054	-0.242
	(0.112)	(0.181)
High-income: omitted category		
IMO Score	0.022***	0.037***
	(0.004)	(0.007)
Olympiad Year FE	Yes	Yes
Observations	1023	1023

Panel B	(1) Pubs (log)	(2) Cites (log)
Income group of origin country:		
Low-income	0.143	0.082
	(0.318)	(0.521)
Lower middle-income	0.175	0.261
	(0.238)	(0.390)
Upper middle-income	-0.354	-0.767*
	(0.264)	(0.432)
High-income: omitted category		
IMO Score	0.020**	0.034**
	(0.009)	(0.015)
Graduate School by Olympiad Year FE	Yes	Yes
Observations	590	590

Notes: These regression are run on the subset of IMO participants who have a PhD in mathematics. The dependent variables are: the log plus one of mathematics publications (column 1), the log plus one of mathematics cites (column 2). The variables of interest are the country income group dummies (high-income omitted) and we control the number of points scored and cohort fixed effects. Panel B also include graduate school by olympiad year fixed effects - comparing participants who participated in the same year and went to the same school for their PhD; the number of observations as some IMO years/graduate school cells only have one observations and are dropped. All regressions are estimated by OLS. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Is the importance of the country of origin diminishing over time?

	(1) Math PhD	(2) Math PhD (top 10)	(3) Pubs (log)	(4) Cites (log)
Income group of origin country:				
Low-income	-0.232***	-0.059**	-0.597***	-0.981***
	(0.038)	(0.024)	(0.094)	(0.155)
Lower middle-income	-0.080***	-0.008	-0.205***	-0.346***
	(0.025)	(0.016)	(0.063)	(0.103)
Upper middle-income	0.017	0.010	0.031	0.007
	(0.028)	(0.018)	(0.070)	(0.116)
Low-income X late cohort	0.101**	0.030	0.346***	0.562***
	(0.043)	(0.027)	(0.109)	(0.179)
Lower middle-income X late cohort	-0.026	-0.022	0.018	0.037
	(0.031)	(0.019)	(0.077)	(0.126)
Upper middle-income X late cohort	-0.082**	-0.055***	-0.157*	-0.247*
	(0.034)	(0.021)	(0.085)	(0.140)
IMO Score	0.011***	0.005***	0.027***	0.046***
	(0.001)	(0.000)	(0.001)	(0.002)
Cohort (Olympiad Year) FE	Yes	Yes	Yes	Yes
Observations	4,711	4,711	4,711	4,711
Mean of D.V.	0.208	0.066	0.415	0.688

Notes: These regressions repeat those of table 7 but include interactions between the country income group and an indicator variable for 'late cohort'. Late cohort takes value one for individuals who participated in the IMO between 1991 and 2000; the omitted category is those who participated between 1980 and 1990. The main effect of late cohort is absorbed in the Olympiad year fixed effects. Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Back of the envelope calculation on the size of lost knowledge production

	Share of IMO	Coeff (pubs)	Coeff (cites)	Loss (pubs)	Loss (cites)
Low-income	0.11	-0.345	-0.571	-0.038	-0.063
Lower middle-income	0.23	-0.197	-0.325	-0.045	-0.075
Upper middle-income	0.23	-0.082	-0.170	-0.019	-0.039
Total				-0.102	-0.177

Notes: This back of the envelope calculation seeks to estimate how much mathematics knowledge production is lost due to developing country participants producing at a lower rate than those of developed countries. To do this we take a weighted sum of coefficients from the main cross-country comparison regressions (7) where the weights are the share of IMO participants in low-income, lower middle-income and upper middle-income countries respectively. This calculation ignores spillovers to other researchers (potentially negative due to crowding out).

Table 12: Comparison with non medalists

	(1) Pubs (log)	(2) Cites (log)	(3) IMC speaker	(4) Fields medalist
Gold medalist	1.2579***	2.1527***	0.0822***	0.0342***
	(0.0968)	(0.1583)	(0.0052)	(0.0011)
Silver or Bronze Medalist	1.1332***	1.8417***	0.0367***	0.0037***
	(0.0513)	(0.0838)	(0.0028)	(0.0006)
Graduate from top 10 schools	0.1130***	0.2648***	0.0098***	0.0005***
	(0.0130)	(0.0212)	(0.0007)	(0.0001)
PhD Graduation Year FE	Yes	Yes	Yes	Yes
Observations	89,068	89,068	89,068	89,068
Mean of D.V.	0.9754	1.6089	0.0040	0.0002
	(1) Pubs (log)	(2) Cites (log)	(3) IMC speaker	(4) Fields medalist
Gold medalist	1.1709***	1.9891***	0.0760***	0.0274***
	(0.1088)	(0.1828)	(0.0080)	(0.0018)
Silver or Bronze Medalist	1.0104***	1.6726***	0.0432***	0.0057***
	(0.0661)	(0.1112)	(0.0048)	(0.0011)
Graduate School by graduation year FE	Yes	Yes	Yes	Yes
Observations	37,501	37,501	37,501	37,501
Mean of D.V.	0.9892	1.6793	0.0070	0.0003

Notes: These regressions are based on an ancillary sample including all math PhD graduates listed in the Math Genealogy Project graduating between 1990 and 2010. The dependent variables are the log plus one of mathematics publications (column 1), the log plus one of mathematics cites (column 2), becoming a speaker at the International Mathematics Congress (column 3) and getting the Fields medal (column 4). The top 10 schools are defined according to the Shanghai Math Ranking and are listed in appendix table A6. All regressions estimated by ordinary least squares. Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

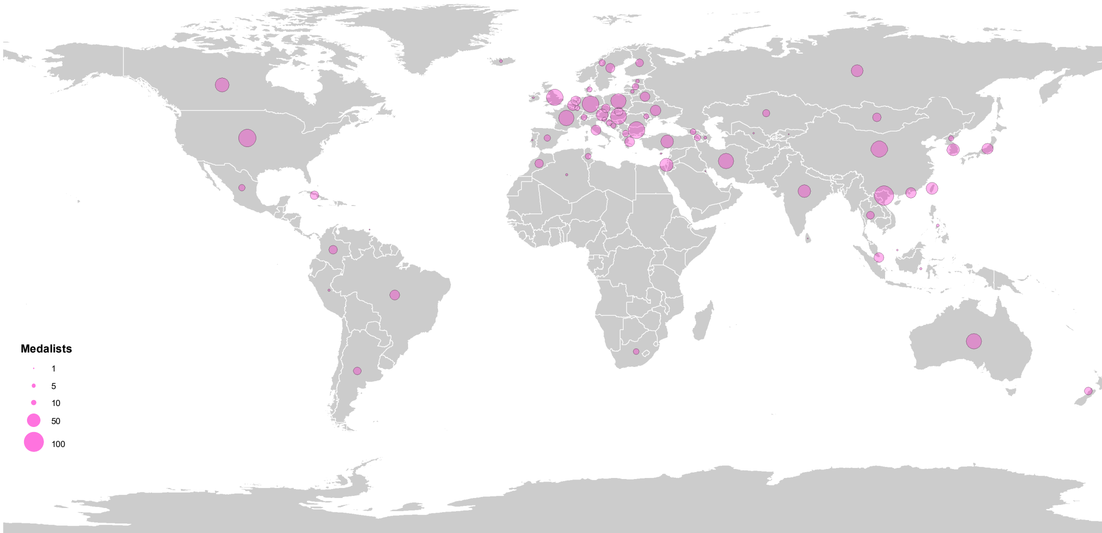
Table 13: Careers outside mathematics

	(1) non-math PhD	(2) non-math web presence (0/1)
Origin country:		
Low-income	0.027*	0.003
	(0.014)	(0.030)
Lower middle-income	-0.006	-0.007
	(0.012)	(0.024)
Upper middle-income	0.026**	0.026
	(0.013)	(0.026)
High-income: omitted		
IMO points	0.001	-0.001
	(0.001)	(0.001)
Cohort Fixed Effects	Yes	Yes
Observations	2273	2273
Mean of D.V.	0.05	0.26

Notes: These regressions are based on the subsample of IMO participants for which we have manually collected information, i.e. all IMO medalists. Having a non-math web presence is an indicator variable that takes value for individuals who (1) we can find on linkedin or have a personal page and (2) do not have mathematics PhD. Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

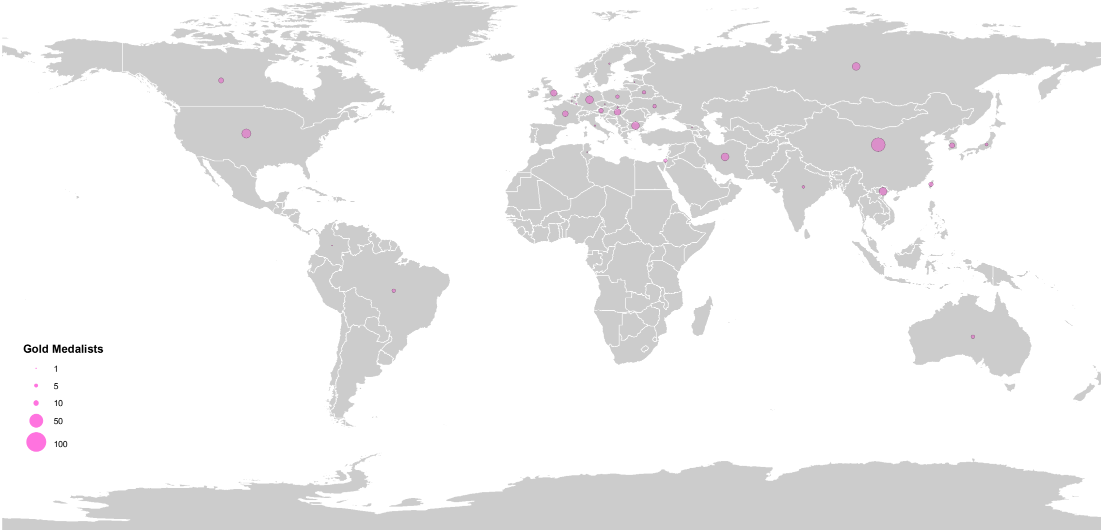
Figures

Figure 1: Medalists by country



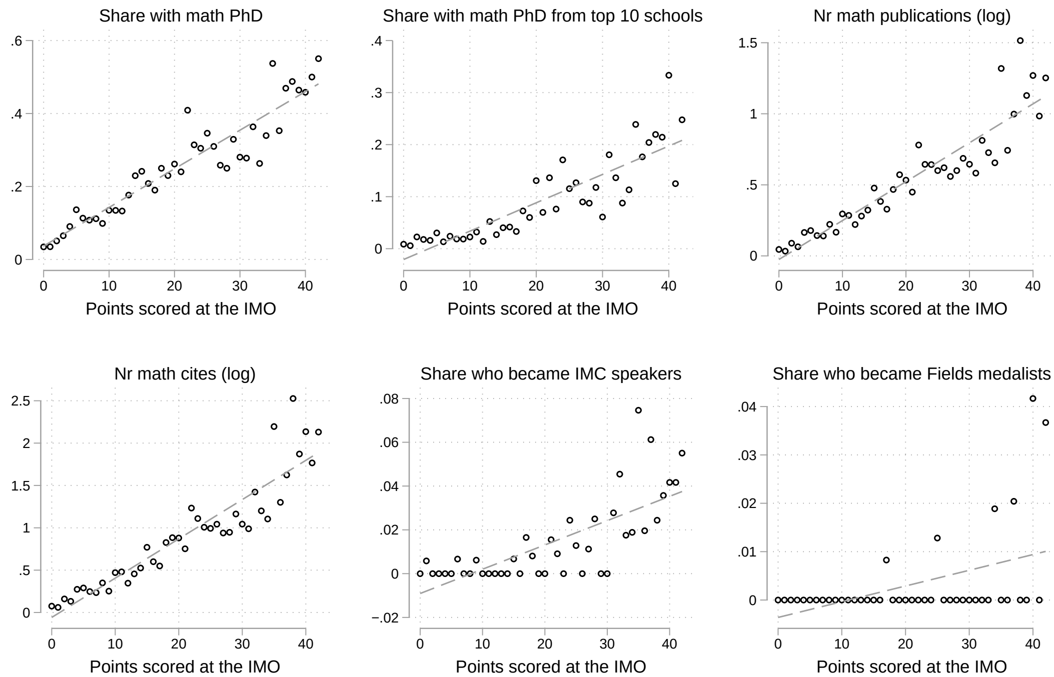
Notes: The figure displays the total number of IMO participants who got a medal between 1981 and 2000 by country.

Figure 2: Gold medalists by country



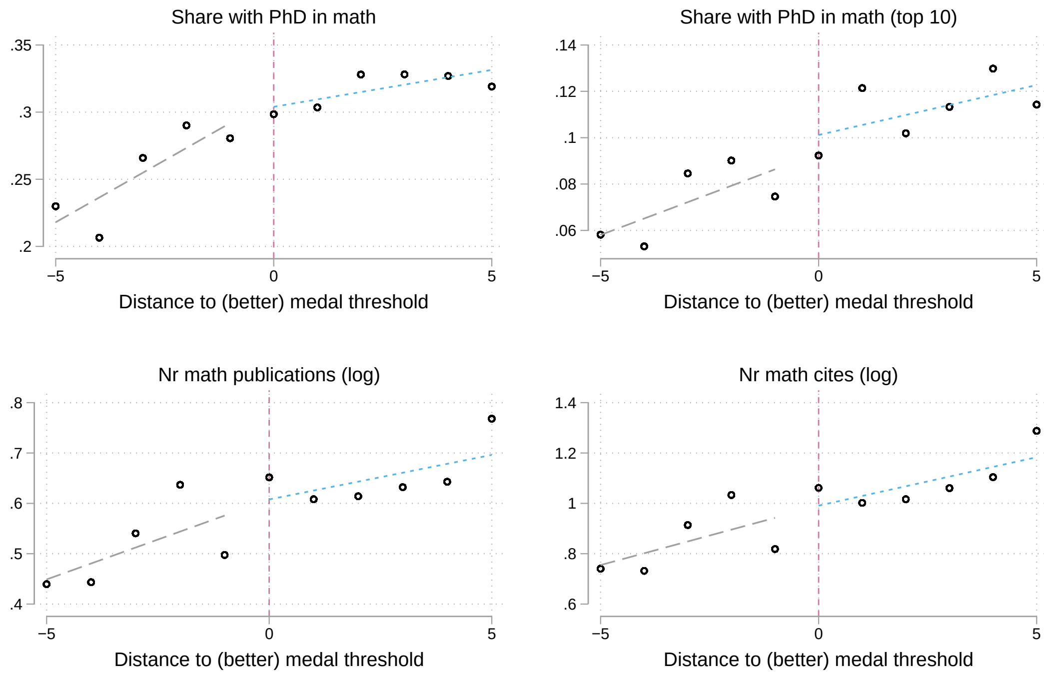
Notes: The figure displays the total number of IMO participants who got a gold medal between 1981 and 2000 by country.

Figure 3: Relationship between points scored at the IMO and subsequent achievement



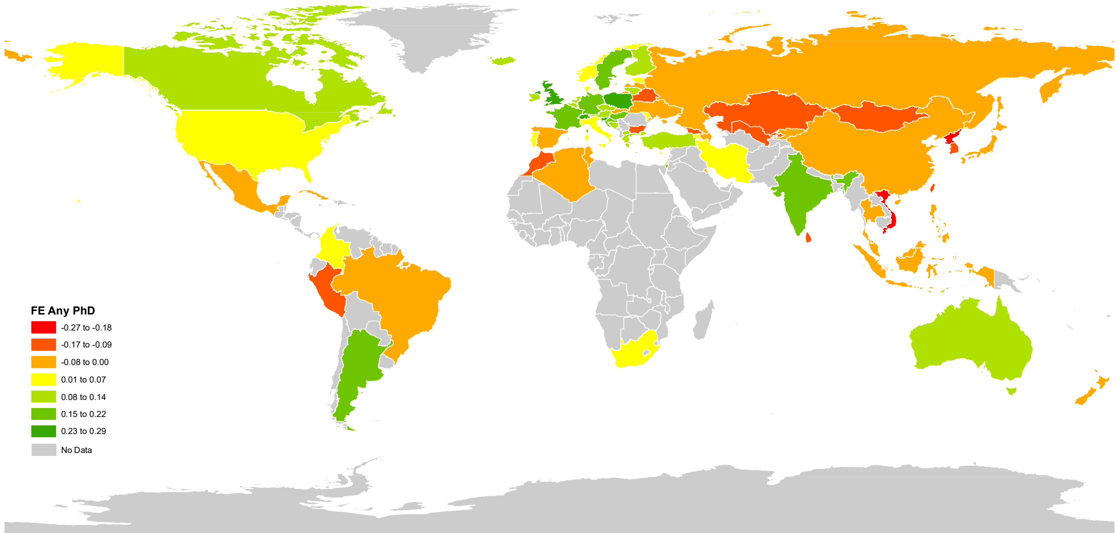
Notes: We compute the sample means of each of the six outcomes variables by the number of points scored at the IMO. We then plot the resulting number against the number of points scored. A linear fit is superimposed.

Figure 4: Distance to medal threshold and long-term performance



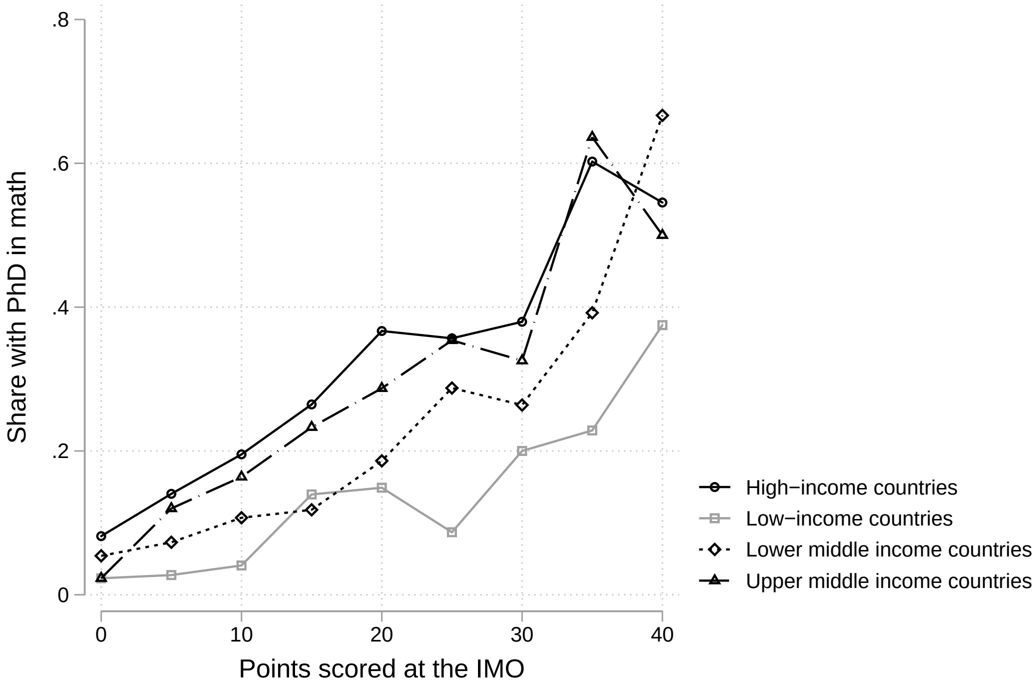
Notes: The IMO medals (gold, silver and bronze) are allocated solely based on the number of points scored at the IMO. The medal thresholds for a gold, silver, or bronze medal vary from year to year. For each medal threshold, we construct the sample of participants no more than 5 points from the threshold. We then stack these three samples and construct a unique distance (number of points) to the threshold for a (better) medal. The graph displays samples means by distance to the threshold for a (better) medal, with linear fits superimposed.

Figure 5: Talent conversion by country



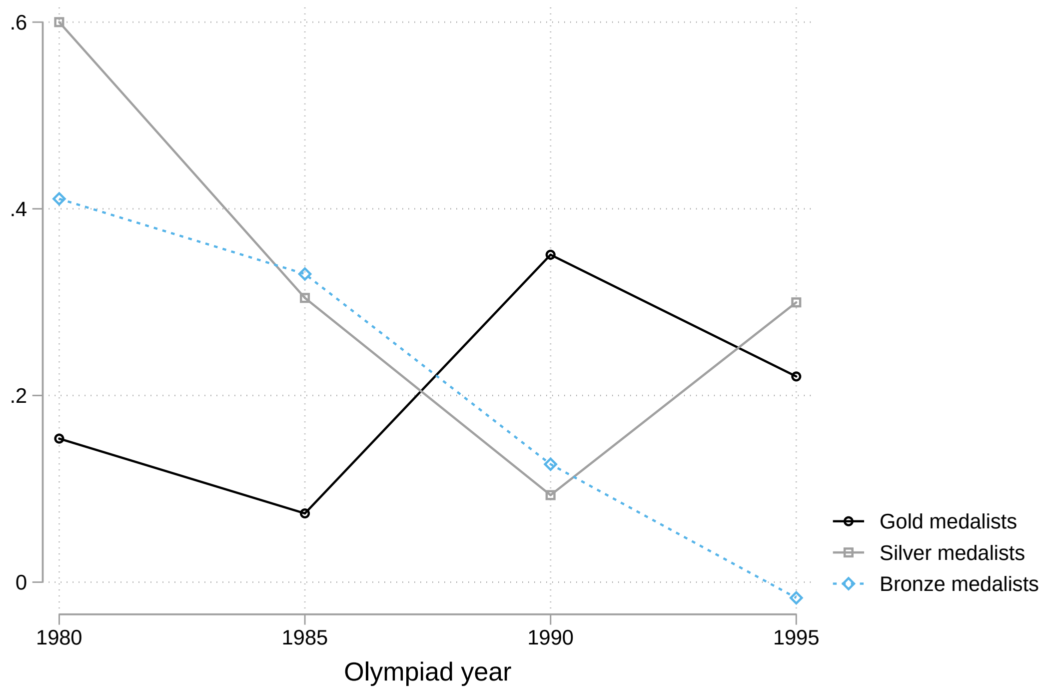
Notes: We first regress the propensity of doing a mathematics PhD on country fixed effects, cohorts fixed effects and points fixed effects. We then plot those country fixed effects. The omitted country in these regressions is the U.S. and thus the fixed effects shown can be thought as relative to the U.S. Countries whose IMO participants have a low propensity of doing a PhD mathematics are shown in red where those countries who have a high propensity of doing a PhD a mathematics are shown in green.

Figure 6: Differences in the share getting a PhD in math across countries



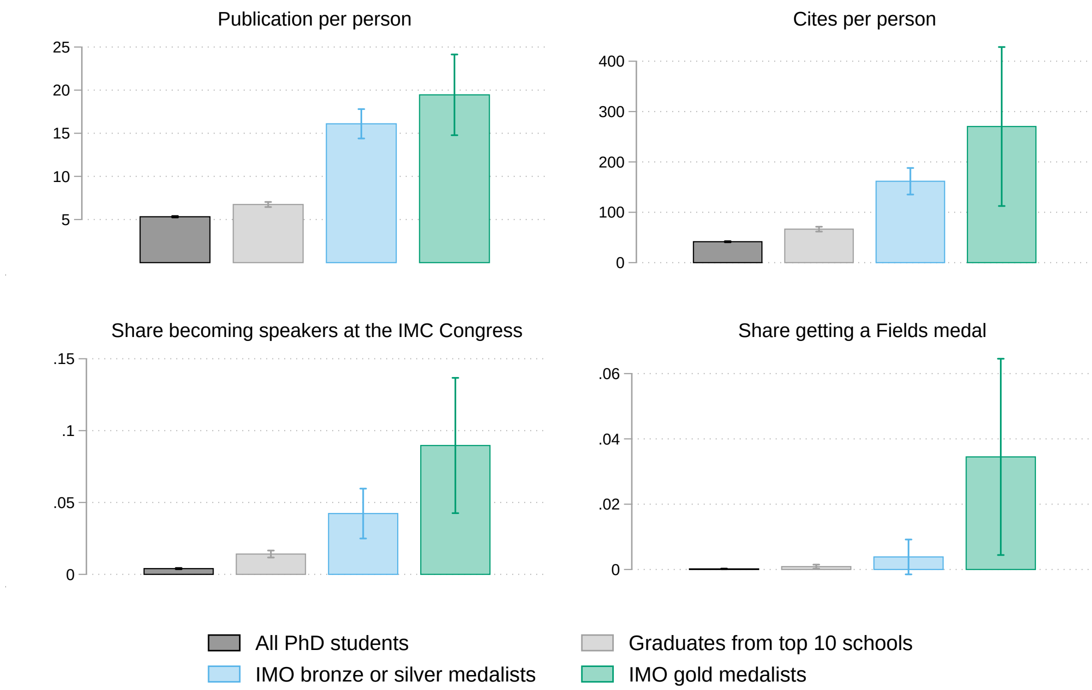
Notes: We compute the share of IMO participants getting a PhD in mathematics by number of IMO points scored (5-year bands) and plot the resulting share against the number of points scored.

Figure 7: Difference in share getting a PhD between high and low income countries for different cohorts of medalists



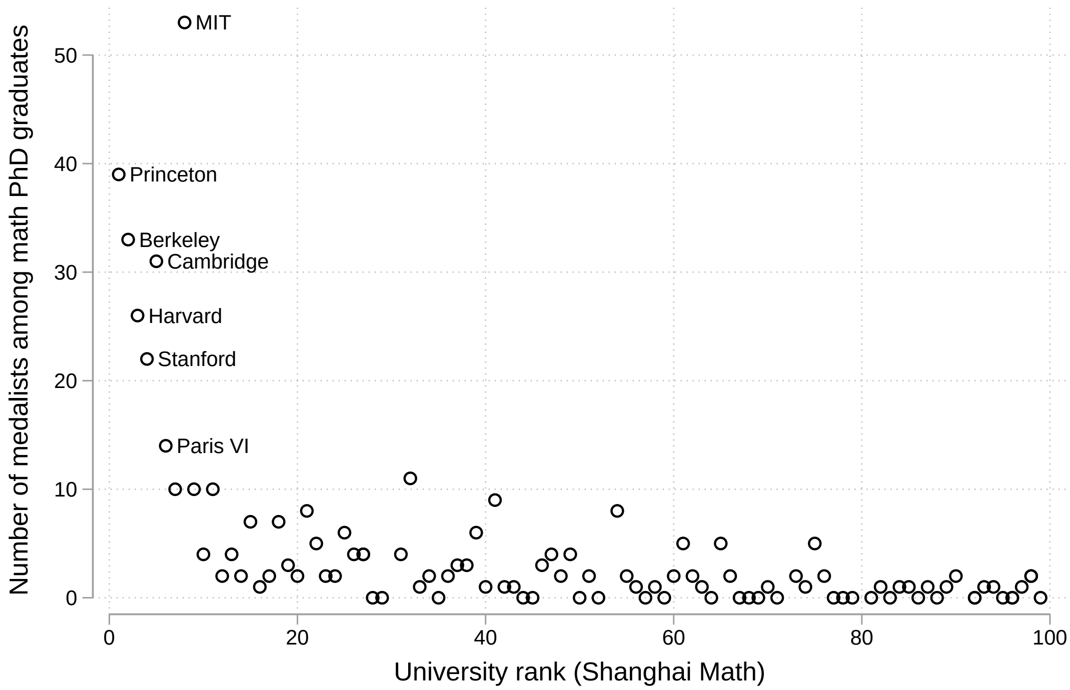
Notes: We compute the share of IMO medalists getting a PhD in mathematics by Olympiad year (5-year band) and medal type. We then plot the result share against Olympiad year.

Figure 8: Comparing IMO medalists with other professional mathematicians



Notes: These figures are based on an ancillary sample including all mathematics PhD graduates listed in the Mathematics Genealogy Project. The graph display sample means across four outcomes (publications, cites, becoming a speaker at the IMC congress, and becoming a Fields medalist) for four groups of PhD graduates (all PhD graduates, PhD graduates from top ten schools, IMO bronze or silver medalists, IMO gold medalists).

Figure 9: Number of IMO medalists graduating from math PhD programs, by graduating school



A Appendix: IMO problems

IMO problems are meant to be solveable without knowledge of higher level mathematics such as calculus and analysis taught at tertiary level. They are typically drawn from geometry, number theory or algebra. Potentials problems are submitted by national mathematical federation and then selected by a problem selection committee from the host country.

Compendia of past problems are available and often used as training by future participants. The topic of the most difficult problems is often discussed on online forums such as Quora.[21]

An example of an 'easy' problem. IMO 1964 Problem 1: (a) Find all natural numbers n such that the number $2^n - 1$ is divisible by 7. (b) Prove that for all natural numbers n the number $2^n + 1$ is not divisible by 7.

The following solution is suggested on the https://artofproblemsolving.com:

"We see that 2^n is equivalent to $2, 4$ and $1 \pmod 7$ for n congruent to $1, 2$ and $0 \pmod 3$, respectively. From the statement above, only n divisible by 3 work. Again from the statement above, 2^n can never be congruent to $-1 \pmod 7$ so there are no solutions for n."

An example of a difficult problem. IMO 1988 Problem 6. Let a and b be positive integers such that $(1 + ab)|(a^2 + b^2)$. Show that $(a^2 + b^2)/(1 + ab)$ must be a perfect square.

Engel (1998:138) recounts the following story regarding this problem.

> "[The] problem was submitted in 1988 by the FRG [Federal Republic of Germany]. Nobody of the six members of the Australian problem committee could solve it. Two of the members were Georges Szekeres and his wife, both famous problem solvers and problem creators. Since it was a number theoretic problem it was sent to the four most renowned Australian number theorists. They were asked to work on it for six hours. None of them could solve it in this time. The problem committee submitted it to the jury of the XXIX IMO marked with a double asterisk, which meant a superhard problem, possibly too hard to pose. After a long discussion, the jury finally had the courage to choose it as the last problem of the competition. Eleven students gave perfect solutions."

[21] See for instance https://www.quora.com/What-according-to-you-is-the-easiest-problem-ever-asked-in-an-IMO or https://www.quora.com/What-is-the-toughest-problem-ever-asked-in-an-IMO

B Appendix: estimating the causal effect of honourable mentions

IMO participants who do not win a medal but solve one problem perfectly (7 points out of 7) receive an honourable mention. To estimate the causal effect of receiving an honourable mention, we rely on the fact that the honourable mention award was introduced at the 1988 IMO (and given out in subsequent years) but did not exist previously. This enables us to identify a set of 'counterfactual honourable mention awardees' that would have received the award if the award existed in the year in which they competed, but did not actually receive the award. While comparing the actual awardees to the counterfactual awardees is conceptually appealing, we must reckon with the fact that the actual and counterfactual awardees necessarily belong to different cohorts. We thus implement a difference-in-differences approach comparing those who solved one problem perfectly before and after the honourable mentions were introduced, using the rest of non-medalists participants as a control group to infer a counterfactual time trend. Specifically, we run regressions of the following type:

$$y_{it} = \alpha + \beta * Scored7_{it} + \delta * Honourable_{it} + \eta_t + \epsilon_{it} \tag{4}$$

where y_{it} is one of obtaining a PhD in mathematics, obtaining a PhD in mathematics from a top 10 school, mathematics publications in logs or mathematics cites in logs. $Score7_{it}$ is an indicator variable for having solved one problem perfectly. $Honourable_{it}$ is an indicator effect for having received an honourable mention. $Honourable_{it}$ also corresponds to the interaction between $Score7_{it}$ and an indicator variable for competing after 1988. Finally η_t is a full set of Olympiad year fixed effects. The sample for these regressions is the set of non-medalists among all IMO participants.

(insert table A1 about here)

The results are displayed in table A1. We find no significant effect of getting an honourable mention. While the estimates are noisy, the point estimate for the effect of getting an honourable mention is actually negative for all four outcomes. We conclude that honourable mentions do not appear to have a causal effect on getting a PhD in mathematics and other mathematics-related career achievements.

C Appendix tables

Table A1: Effect of obtaining a honourable mention at the IMO

	(1) Math PhD	(2) Math PhD (top 10)	(3) Pubs (log)	(4) Cites (log)
Honourable mention	-0.0550	-0.0238	-0.0443	-0.0769
	(0.0357)	(0.0170)	(0.0764)	(0.1259)
Perfect score	0.0613*	0.0320**	0.0678	0.1124
on one problem	(0.0313)	(0.0149)	(0.0669)	(0.1104)
Observations	2,438	2,438	2,438	2,438
Adjusted R2	0.0021	0.0029	0.0059	0.0060

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: IMO score by country income group

	(1) IMO Score
Income group of origin country:	
Low-income	3.204***
	(0.534)
Lower middle-income	0.621
	(0.404)
Upper middle-income	0.028
	(0.444)
High-income: omitted category	
Cohort (Olympiad Year) FE	Yes
Observations	4711
Mean of D.V.	16.008

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: IMO score, long-term performance and GDP per capita of the origin country

	(1) Math PhD	(2) Math PhD (top 10)	(3) Pubs (log)	(4) Cites (log)
GDP per capita	0.003***	0.001***	0.006***	0.011***
(1000 USD)	(0.000)	(0.000)	(0.001)	(0.001)
IMO score	0.011***	0.006***	0.027***	0.046***
	(0.001)	(0.000)	(0.001)	(0.002)
Cohort (Olympiad Year) FE	Yes	Yes	Yes	Yes
Observations	4,379	4,379	4,379	4,379
Mean of D.V.	0.211	0.068	0.415	0.689

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. GDP per capita is as of 2000 and expressed in thousands of U.S. dollars.

Table A4: Link between IMO score and long-term performance by country income deciles

	(1) Math PhD	(2) Math PhD (top 10)	(3) Pubs (log)	(4) Cites (log)
Decile 1 (poorest)	-0.1372***	-0.0463***	-0.2377***	-0.4025***
	(0.0230)	(0.0145)	(0.0576)	(0.0944)
Decile 2	-0.1279***	-0.0345**	-0.2543***	-0.4151***
	(0.0241)	(0.0152)	(0.0604)	(0.0990)
Decile 3	-0.0767***	-0.0243*	-0.1816***	-0.2957***
	(0.0233)	(0.0146)	(0.0583)	(0.0955)
Decile 4	0.0032	-0.0066	0.0280	0.0383
	(0.0229)	(0.0144)	(0.0573)	(0.0939)
Decile 5	0.0409*	-0.0315**	0.1447**	0.1938**
	(0.0239)	(0.0150)	(0.0597)	(0.0978)
Decile 6	-0.0015	-0.0149	0.0381	0.0468
	(0.0235)	(0.0147)	(0.0587)	(0.0962)
Decile 7	-0.0678***	-0.0098	-0.1341**	-0.2216**
	(0.0235)	(0.0147)	(0.0587)	(0.0961)
Decile 8	0.0538**	-0.0154	0.1506***	0.2725***
	(0.0224)	(0.0141)	(0.0560)	(0.0918)
Decile 9	0.0962***	0.0089	0.2531***	0.4299***
	(0.0232)	(0.0146)	(0.0581)	(0.0953)
Richest decile omitted				
IMO score	0.0106***	0.0053***	0.0258***	0.0430***
	(0.0005)	(0.0003)	(0.0013)	(0.0022)
Cohort (Olympiad Year) FE	Yes	Yes	Yes	Yes
Observations	4,711	4,711	4,711	4,711
Mean of D.V.	0.211	0.068	0.415	0.689

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The income deciles are computed based on 2000 GDP per capita.

Table A5: Controlling for scientific and mathematics articles of the origin country

	(1) Math PhD	(2) Math PhD (top 10)	(3) Pubs (log)	(4) Cites (log)
Scientific articles of origin country (log)	0.004	0.007	-0.020	-0.030
	(0.008)	(0.005)	(0.020)	(0.033)
Math articles of origin country (log)	0.010	-0.000	0.049**	0.077**
	(0.009)	(0.006)	(0.022)	(0.037)
Low-income	-0.134***	-0.020	-0.318***	-0.535***
	(0.024)	(0.015)	(0.059)	(0.098)
Lower middle-income	-0.073***	-0.010	-0.150***	-0.256***
	(0.019)	(0.012)	(0.047)	(0.078)
Upper middle-income	-0.022	-0.026**	-0.050	-0.128*
	(0.017)	(0.011)	(0.044)	(0.072)
High-income: omitted category				
IMO Score	0.010***	0.005***	0.025***	0.043***
	(0.001)	(0.000)	(0.002)	(0.003)
Cohort (Olympiad Year) FE	Yes	Yes	Yes	Yes
Observations	4300	4300	4300	4300
Mean of D.V.	0.214	0.069	0.423	0.702

Notes: These regressions mirror those of table our main result table 7 but add two additional country level controls: the number of scientific articles produced by the country (as of 2000, in logs) and the number of mathematical articles produced by the country (as of 2000, in logs). The dependent variables are as follows: obtaining a math PhD (column 1), obtaining a math PhD from a top 10 school (column 2), the log plus one of mathematics publications (column 3), the log plus one of mathematics cites (column 4). All regressions are estimated by OLS, control for the number of points scored at the IMO and include cohort (olympiad year) fixed effects. Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Top ten schools in mathematics according to the 2010 Shanghai (ARWU) subject ranking

University	**Rank**
Princeton University	1
University of California, Berkeley	2
Harvard University	3
Stanford University	4
University of Cambridge	5
Pierre and Marie Curie University (Paris 6)	6
University of Oxford	7
Massachusetts Institute of Technology	8
University of Paris Sud (Paris 11)	9
University of California, Los Angeles	10