Finding Talent at Scale: Evidence from Rwanda's Mathematics Olympiad*

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Abstract

Science competitions can only discover the talent they observe. If participation depends on access to schools, teachers, and local institutional support, then even highly effective competitions may systematically overlook talented individuals. This challenge is likely to be particularly acute in low- and middle-income countries, where talent is often geographically dispersed and resource constraints make it more difficult for national programs to reach all schools and students. We study the early expansion of the Rwanda Mathematics Olympiad (RMO), a national talent-search program that has rapidly grown since its launch in 2019. We assemble a novel dataset covering the universe of lower secondary schools in Rwanda, linked to RMO participation and performance between 2023 and 2025, to examine which schools participate, where high-performing students are found, and how much talent remains outside the competition. We document three main findings. First, participating schools are larger, more science-oriented, and substantially higher performing on national examinations than non-participating schools. Second, national examination performance is by far the strongest predictor of a school producing high-performing Olympiad participants. Third, as the RMO expands, it primarily reaches middle-performing schools, substantially broadening the pool of talented students. Using predicted participation patterns, we estimate that non-participating schools currently contain approximately 16,000 potentially high-performing students who remain outside the Olympiad system. These findings suggest that talent-search institutions shape not only how talent is developed, but also who is identified in the first place. More broadly, the paper highlights institutional interactions as a source of inequality in the pipeline to science and innovation.

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1 Introduction

Brazilian mathematician Artur Avila, who was awarded the Fields Medal in 2014 for his groundbreaking contributions to dynamical systems, first emerged as an exceptional mathematical talent through mathematics competitions. At age 13, encouraged by a teacher, he entered the junior division of Brazil's Mathematical Olympiad, where he encountered a new style of challenging problem-solving that initially left him feeling unprepared. Reflecting on the experience, Avila recalled, "For the first time, I felt I couldn't do anything." Rather than discouraging him, the competition motivated him to improve. With continued mentorship, he won the state-level competition the following year, and by age 16 earned a gold medal at the International Mathematical Olympiad (IMO) in 1995.[1]

From this example, and plenty others like it, performance in international science competitions during early years, like the International Mathematics Olympiad (IMO), strongly predicts later scientific achievement (Agarwal and Gaule, 2020). Competition performance can therefore provide a useful signal of future potential, which can then be used to allocate opportunities and development. Once identified, students can access training, mentorship, scholarships, and international opportunities. Given that innovation and long-run economic growth depend on identifying and developing high-potential individuals (Freeman and Van Reenen, 2009; Jones, 2002), these kinds of competitions can play an important role in domestic and international talent pipelines and innovation ecosystems.

But, this example and existing research on the relationship between competition performance and long-run outcomes tell us more about the talented individuals who are observed in a talent identification system than those who are not. In practice, not all high-ability individuals are equally likely to be discovered through these systems. Plenty of prior research has documented the fact that while that talent is broadly distributed, opportunities are not. Family background, geography, and unequal educational opportunities shape who becomes inventors and scientists (Bell et al., 2019; Hsieh et al., 2019; Agarwal and Gaule, 2020). Participation in competitions like the IMO is no different. While the competition is now global, it was long dominated by Eastern European and high-income countries, with many countries in Sub-Saharan Africa and South Asia joining only in recent decades.[2] Even now, because only a small number of students represent each country at the IMO, inequalities in access to training and competition pathways are likely to shape who ultimately participates. This is particularly true in low- and middle-income countries, where resource constraints often limit opportunities to develop mathematical talent beyond the core curriculum (Kremer, 2003; Agarwal and Gaule, 2026). As a result, many highly capable individuals may remain invisible to institutions that could support them.

One response to this issue has been the expansion of decentralized talent-identification infrastructure through National Mathematical Olympiads. Because the IMO itself only admits six

[1] https://www.quantamagazine.org/artur-avila-is-first-brazilian-mathematician-to-win-fields-medal-20140812/ Last accessed 6.26.26

[2] https://www.imo-official.org/countries/ Last accessed 6.26.26

students per country, national programs play a critical gatekeeping role, identifying and training students who they then nominate to represent their countries internationally. Over the last several decades, these systems have spread rapidly, with more than 100 countries having some version of a national competition search program. National Olympiad programs, often supported by governments and universities, have the potential to broaden the search for talent by reaching more schools, regions, and socioeconomic groups. In doing so, they can serve a dual purpose of identifying and nurturing talent. Whether they actually succeed in expanding the talent pool, however, depends on how effectively they reach talented students.

In particular, in many LMIC contexts, National Olympiads are embedded in broader talent-development ecosystems that span classrooms, extracurricular preparation, national selection processes, and coaching networks. Within these ecosystems, school-based teachers in particular play distinct roles. Teachers may act as frontline talent scouts and motivators, often providing substantial informal support beyond formally coordinated activities, such as encouraging students to engage in the program, creating additional time for problem-solving, organizing study groups, sharing or adapting learning resources, and encouraging students to persist. But because school-based approaches rely on teachers, schools, and local support structures that are themselves unevenly distributed, they may inadvertently reproduce existing inequalities. Students in under-resourced schools, remote areas, or schools lacking motivated teachers may never enter the pipeline. This raises a central question: to what extent do National Mathematical Olympiads identify talented students across the full talent distribution, and which schools and students remain outside the system?

The recent creation and rapid growth of the Rwanda Mathematics Olympiad provides an opportunity to study these questions. The Rwanda Mathematics Olympiad was launched in 2019 through a partnership between the African Institute for Mathematical Sciences (AIMS Rwanda), the University of Rwanda, and the Ministry of Education. The program combines nationwide competitions, which it administers in collaboration with local schools, with residential training camps that prepare students for regional and international contests, including the Pan-African Mathematics Olympiad (PAMO) and the International Mathematical Olympiad (IMO). The Rwanda Mathematics Olympiad (RMO) has rapidly scaled, reaching more than 50,000 students across 900 schools by 2026. But that said, a large proportion of Rwandan schools and therefore students remain uninvolved in the RMO competition, potentially limiting the identification of highly talented individuals in the country.

In this paper we study the reach and the early expansion of the Rwanda Mathematics Olympiad. By tracing how participation spreads across schools, we are able to quantify how much mathematical talent remains undiscovered because schools do not participate. In doing so, we assess whether expansion of a national talent search program reduces the stock of undiscovered talent. We build a new dataset that covers the universe of lower secondary schools in Rwanda, matched to RMO participant scores and persistence through rounds of competition between 2023 and 2025. We leverage information on school characteristics to document three facts. First, schools participating

in the RMO tend to be higher performing schools on national exams, and larger schools that are more science focused compared to schools that don't participate in the RMO. Interestingly, they are equally likely to be rural schools, have internet access and have similar governance structures. Second, schools that are more likely to have higher performing students on the RMO are particularly likely to be higher performing schools on national exams, and in fact, that national exam scores are by far the strongest predictor of having high performing RMO students. Third, between 2024 and 2025, the RMO expanded by adding more middle performing schools, but at the same time, several high performing schools dropped out. Our estimates suggest that by not including a large number of schools that perform in the middle of the distribution in terms of national exams in particular, the RMO is potentially 'missing' more than 16,000 potentially high performing Rwandan students in the competition.

In the coming months, we will link participating students to Ministry of Education teacher records to identify teacher characteristics associated with RMO participation and success. Building on these findings and qualitative interviews, we are also designing a randomized controlled trial to test interventions that increase teacher engagement in the RMO by addressing barriers such as information frictions, weak incentives, and limited support.

We contribute to two main literature streams. First, we contribute to a growing literature on who becomes inventors and scientists by highlighting the role of talent-search institutions. Whereas prior work emphasizes how family background and geography shape the development of talent (Akcigit et al., 2017; Bell et al., 2016; Agarwal and Gaule, 2020), we show that institutional infrastructure also determines who is identified in the first place. Talent-search systems mediate the translation of underlying ability into opportunity, and their effectiveness depends on the institutions through which they operate, such as schools. As a result, unequal access to talent identification represents a previously overlooked source of inequality in the innovation pipeline, with important implications for who ultimately becomes an inventor or scientist.

Second, we contribute to an emerging literature on science competitions and their role in innovation pipelines. Existing work focuses largely on the careers of participants and interventions that improve performance (Agarwal and Gaulé, 2017; Agarwal and Gaule, 2020, 2026; Moreira and Estevan, 2026; Calaway, 2024). We shift attention to the participation margin and the process through which talent is brought into the pipeline.

2 The Rwanda Mathematics Olympiad

The International Mathematical Olympiad (IMO) is the most well-known international mathematics competition from secondary school students. Started in Romania in 1959, with seven Eastern European participants, it has since expanded to include more than 100 countries. Many nations have established National Mathematical Olympiads (NMOs) to identify and train students for regional and international competitions. These typically narrow down students from first rounds which include large number of students at local levels, to smaller numbers participating at national

competitions and training levels.

When Rwanda launched its National Mathematics Olympiad program in 2019, national Olympiad systems were still relatively uncommon in Africa. At the time, only around a dozen countries were regularly represented in the Pan-African Mathematics Olympiad, suggesting that roughly 10–15 countries had established National Mathematics Olympiads or comparable talent identification systems. Since then, participation has expanded substantially, with more than 30 countries represented at PAMO and 10 countries participating in the IMO by 2023. Rwanda itself began sending students to the IMO in 2021, and its results have improved over time, moving from 101st place in 2021 to 92nd in 2025.[3]

The RMO is structured as a multi-stage process: schools register students, an initial round is administered locally, top performers advance through district and national rounds, and the strongest students are invited to residential training camps that ultimately select Rwanda's teams for PAMO and the IMO. There are junior and senior competitions, with junior competitions accessible to lower secondary students. The junior competition is larger, and so for the purposes of this paper we focus on that competition. Participation has expanded rapidly since its founding, from a small pilot in 2019 to more than 38,000 junior students participating annually by 2024 and nearly 57,000 students in the first round of the 2025–26 cycle, with finalists drawn from schools across all districts and increasing representation from rural areas.

The expansion of the RMO gives an opportunity to examine talent search systems in their early stages. In this paper we ask three research questions:

1. *Which schools participate in the Rwanda Mathematics Olympiad in its early years? How does participation vary by school quality, rurality, and local infrastructure?*

2. *How much mathematical talent remains undiscovered because schools do not participate?*

3. *Has expansion of the Rwanda Mathematics Olympiad reduced the stock of undiscovered talent over time? Has expansion disproportionately benefited previously underrepresented groups?*

3 Data

In this section we describe the data that we combined across several sources to create a novel dataset used in our analysis.

3.1 Rwanda Mathematics Olympiad Data

In this paper, we focus on the lower secondary school competition in the Rwanda National Mathematics Olympiad, the Junior Rwandan Mathematics Olympiad (JRMO). This competition consists of three rounds which increase in difficulty and selectivity. Students who perform well and advance through all three rounds are invited to regional math camps and may be tapped to represent Rwanda at the IMO.

[3] https://www.imo-official.org/results/team/country/RWA/

We use administrative records from the RMO covering the 2023, 2024, and 2025 competition years.[4] The dataset includes student-level participation records with competition performance and progression through competition stages, including scores in initial rounds, and advancement through rounds. Crucially, each student record is linked to their school and teacher names. This structure allows us to connect individual performance to school level data (see next sub-section), and to study how talent identification operates within and across schools over time. In particular, we can identify which schools entered students each year, how many students they entered, the extent of repeat participation over time, and the performance of students at different types of schools, allowing us to track the diffusion of Olympiad engagement across the school system.

3.2 Ministry of Education Administrative Data

We link the RMO records to administrative data from Rwanda's Ministry of Education (MINEDUC). The MINEDUC data provide school-level characteristics for the universe of lower secondary schools in Rwanda (2,693 schools), including total lower secondary enrollment, teacher counts, classroom counts, computer availability, internet access, school location (rural or urban), school type (government-aided, public, or private), science-school designation, and district identifiers. For 2024, we also have the average student score on the Ordinary Level National Exam (OLNE), the lower secondary school exit exam, at the school level. While this paper is primarily focused on high ability students, this school-level measure provides important information on the ability distribution of a given school. We also have recently gained access to teacher level data from MINEDUC and intend to match student performance to teacher characteristics (including teacher education and experience) in the next version of this paper.

Our final database covers the universe of lower secondary schools in Rwanda. From the right hand columns in Table 1, we can see that schools participating in JRMO are very likely to be rural schools, with around 350 students, and the majority have internet access and are science-focused, government aided schools. As can be seen in the bottom rows of Table 1, participating schools sent on average 57 students each per year to participate in the JMRO, with around 13% of students progressing into round 2, and 0.8% of students progressing to round 3. This drop-off is consistent with popular talent search mechanisms. Figure 1 demonstrates that the number of schools participating is rising over the observation period, raising the question of how effectively this expansion is capturing the talent base in the country.

4 Rwandan Schools and Math Talent

Because we are interested in the extent to which national talent identification systems capture the available talent base, we begin by describing Rwandan schools by their JRMO participation status. We show that participating and non-participating schools have some similarities, and importantly

[4] Unfortunately, data on competition performance prior to 2023 was not accessible to us.

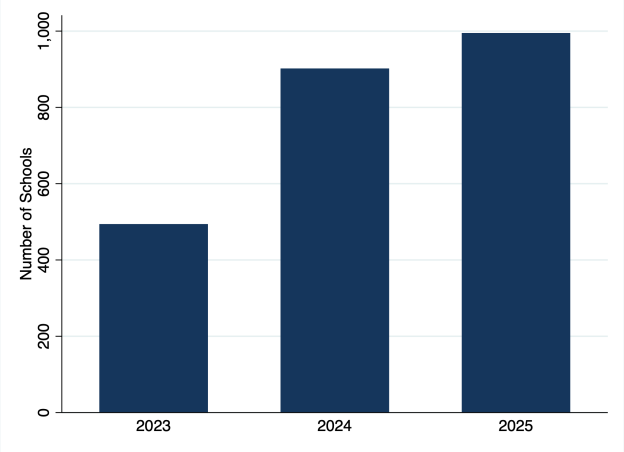


Figure 1: This figure shows the number of lower secondary schools participating in the RMO each year.

that a substantial number of high-performing schools (as measured by national exam results) do not participate in the RMO.

However, this pattern alone is not necessarily informative about the extent to which highly talented individuals are captured by the system. To better understand this, we examine the students who progress through the competition rounds (i.e. top talent) and the characteristics of the schools they come from, allowing us to assess whether non-participating schools are likely to contain top talent who are systematically missed by the system. We show that national exam performance is the strongest predictor of exceptional performance in the competition.

Finally, to assess whether expansion of the search system ameliorates or exacerbates selection challenges, we examine how school participation evolves between 2024 and 2025. While the reach of the competition increases, this mostly seems to be at the middle of the performance distribution. But at the same time, there is attrition of schools in the middle of the performance distribution, and a large number of schools lower in the distribution never participate. Finally we construct a rough approximation of potential top talent at non-participating schools.

4.1 Selection into Competition

Table 1 presents summary statistics separately for the schools participating in the JRMO and the non-participants across the three years (2023-2025 inclusive). The two groups are broadly comparable. Participating and non-participating schools have similarly likely to be based in rural areas (84 and 85 percent, respectively), although participating schools have slightly lower levels of internet access, and are more likely to be government aided schools, rather then private schools. The most notable differences are in national exam performance and academic orientation: participating schools score 0.20 standard deviations above the national mean on the OLNE while non-participating schools score 0.09 standard deviations below. Participating schools are also larger on average (325 versus 299 lower secondary students) and more likely to be science-focused (69 versus

54 percent).

	No RMO		RMO	
	Mean	SD	Mean	SD
OLNE Performance (Std., 2024)	-0.09	0.89	0.20	1.20
Lower Secondary Students	299.69	176.86	325.73	174.77
Rural School	0.85	0.36	0.84	0.36
No Internet Access	0.23	0.42	0.19	0.39
Science-Focused School	0.54	0.50	0.69	0.46
Government-Aided School	0.54	0.50	0.61	0.49
Private School	0.08	0.27	0.03	0.18
Public School	0.38	0.49	0.36	0.48
Participants (Round 1)	.	.	57.50	59.20
Advancers (Round 1)	.	.	13.23	19.16
Participants (Round 2)	.	.	14.03	21.64
Advancers (Round 2)	.	.	0.77	2.89
Participants (Round 3)	.	.	0.75	2.81
Observations	5,688		2,391	

Table 1: This table provides summary statistics for Rwandan lower secondary schools by JRMO participation status at the school-year level (2023-2025). Columns 1–2 report means and standard deviations for schools that did not participate in the JRMO; Columns 3–4 report the same for those that did participate.

Figure 2 shows the number of schools participating in the 2024 JRMO along the OLNE performance distribution.[5] In general, the distribution of all schools is right-skewed, with the majority of schools concentrated within one standard deviation of the mean, and fewer schools outperforming the rest. JRMO participants are present throughout the distribution, and the number of schools participating and non-participating overlap substantially across most of the performance range. That said, visually there appear to be more non-participating schools in the lower parts of the distribution (amongst the worse performing schools), and once the distribution is around two standard deviations above the mean, a meaningfully higher participation share emerges. In other words, the very top performing schools in the OLNE exam are more likely to participate in the JRMO than not. Together with the summary statistic table it is clear that schools that participate in JRMO are more likely to be higher performing schools than those that do not participate. However, whether this pattern is substantively meaningful in terms of how much talent is captured by the RMO depends on whether these are also top-performing *JRMO schools*, an issue we address in the next sub-section.

[5]We narrow to the 2024 sample only for two reasons. First - the OLNE performance data is only for 2024; Second - we run an exercise later where we observe a school's trajectory from 2024 to 2025, using 2024 as the baseline year.

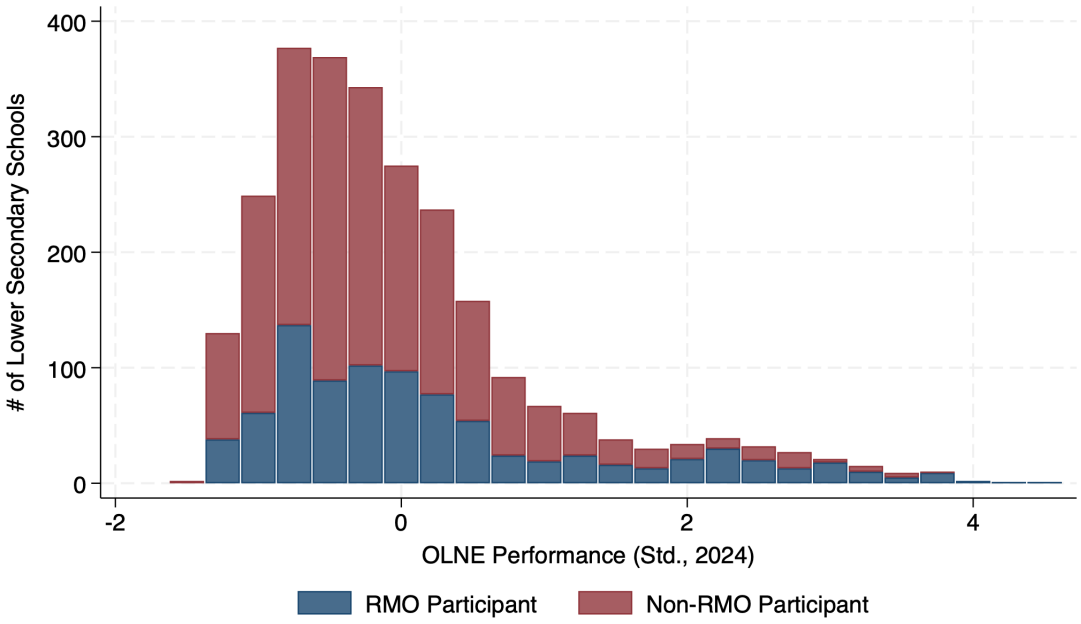


Figure 2: This figure shows the distribution of lower secondary schools by Ordinary National Exam Performance and RMO participation status in 2024. Each bar represents the number of schools in a 0.25 standard deviation bin of school-average OLNE performance, standardized to have mean zero and unit standard deviation across all lower secondary schools in Rwanda. Navy bars correspond to JRMO participants; maroon bars correspond non-participants.

4.2 Estimating a Talent Prediction Model

We next estimate a model predicting progression through JRMO rounds (round 2–R2Q and round 3–R3Q) as a function of school-level observables. More specifically, at the school level we regress student counts in each competition round for each year of competitions on standardized OLNE performance, log lower secondary enrollment, and indicators for rural location, absence of internet access, science-school designation, and governance type, with district and year fixed effects:

$$y_s = \alpha + \beta \text{OLNE Performance}_s + X_s\lambda + \epsilon_s + \sigma_t \tag{1}$$

Where y_s is the number of students in each round, and X_s are school level covariates. Table 2 presents OLS estimates for both R2Qs and R3Qs, with and without OLNE score as a predictor.

	Advancers (Round 1)		Advancers (Round 2)	
OLNE Performance (Std., 2024)		8.8237***		0.7495***
		(0.3175)		(0.0547)
Student Count (log)	-1.5607**	2.7026***	-0.1319	0.2089*
	(0.7873)	(0.7121)	(0.1218)	(0.1226)
Rural School	-2.6125**	1.8768*	-0.2778	0.0955
	(1.2154)	(1.0934)	(0.1881)	(0.1882)
No Internet Access	-2.6480**	0.4244	-0.0701	0.1799
	(1.0311)	(0.9121)	(0.1596)	(0.1570)
Science-Focused School	5.1840***	-1.4690*	0.3393**	-0.1904
	(0.9224)	(0.8469)	(0.1428)	(0.1458)
Government-Aided School	-0.3664	-0.2972	0.1826	0.2014
	(0.8907)	(0.7889)	(0.1378)	(0.1358)
Private School	7.2758***	-0.8026	1.3832***	0.7406**
	(2.2932)	(2.0333)	(0.3549)	(0.3500)
Mean of Dep. Var.	13.2300	13.2518	0.7687	0.7755
N	2391	2343	2391	2343
Adj. R^2	0.0706	0.3046	0.0212	0.0963

All specifications include district and year fixed effects.

Standard errors in parentheses.

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

Table 2: This table presents OLS estimates of Equation 1. The outcome is the number of Round 2 Qualifiers (R2Qs; Columns 1–2) and Round 3 Qualifiers (R3Qs; Columns 3–4). Odd columns exclude school-average OLNE performance; even columns include it. All specifications include district and year fixed effects. Standard errors in parentheses.

As the results demonstrate, national exam performance is the most notable predictor of RMO success. A one standard deviation increase in school-average OLNE score is associated with 8.82 additional R2Qs ($p < 0.01$). Including average OLNE performance to the baseline specification

raises the adjusted R^2 from 0.08 to 0.30, a near-fourfold improvement in explanatory power, while greatly reducing the size and significance of coefficients on other predictors. In our preferred specification with average OLNE performance, school enrollment is positive and marginally significantly for R2Qs. This is consistent with larger schools having more draws from a talent distribution.

To better quantify the relative contribution of each predictor, Table 3 shows a dominance analysis that assigns each predictor its average marginal contribution to R^2 across all possible model subsets. School-average OLNE performance accounts for 76% of total explained variance. District fixed effects contribute an additional 13%. All remaining school characteristics, including enrollment, rurality, internet access, science designation, and governance type, together account for less than 6%.

	results % of R^2	Rank
OLNE Peformance	76.72	1
Student Count (log)	.86	8
Rural School	1.32	6
No Internet Access	.97	7
Science-Focused School	2.87	3
Government-Aided School	.24	9
Private School	1.4	5
District FEs	13.32	2
Year FEs	2.3	4

Table 3: This table presents a dominance analysis of R2Qs among 2024 JRMO participants. Each row reports the average marginal contribution of the listed predictor to the model R^2, expressed as a percentage of total explained variance, alongside the predictor's dominance rank. District fixed effects are included as a set.

Taken together, these results provide evidence on the extent to which the talent identification system may miss potentially high-performing students. While school-average OLNE performance strongly predicts progression through the competition rounds, we saw in the figure above that a non-trivial number of high-performing schools do not participate in the JRMO. This pattern suggests that the set of observed participants may not fully reflect the underlying distribution of academic ability across schools, implying that some potentially talented students may not be reached by the current search process.

4.3 Expansion and Attrition

Despite overall expansion across schools in Rwanda over the years, between 2024 and 2025 each school follows one of four trajectories: participating in both years (*Returning*), participating in 2024 but not 2025 (*Departing*), not participating in 2024 but joining in 2025 (*Entering*), or remaining outside the competition in both years (*Never Participating*). Returning schools represent the stable core of the competition; Departing schools signal attrition that may reflect discouragement

or organizational disruption; Entering schools represent the competition's expansion into previously unreached populations; and Never Participating schools constitute the universe of potential talent the JRMO has not yet touched.

Figure 3 plots the number of schools in each category across the OLNE distribution. Visually, it appears as though Never Participating schools dominate the left half of the distribution, suggesting that the JRMO is never reaching these lower performing schools. Both Entering and Departing schools are most prevalent near the mean, where both recruitment and attrition are most active. In the right tail, above approximately +1.5 standard deviations, Returning schools dominate and Never Participating schools become rare—the JRMO has largely already reached the highest-performing schools, and those schools tend to stay. The implication for outreach is that the remaining opportunity lies not at the top of the performance distribution but in the broad middle, where schools are capable of producing individuals that progress through the rounds, but have not been consistently reached or retained.

Taken together, this suggests that program expansion has been primarily horizontal and middle-out rather than a systematic shift toward lower-performing schools. The JRMO appears to have already captured most high-performing schools, and further expansion is occurring mainly within the broad middle of the performance distribution rather than meaningfully extending the right tail or fully penetrating the left tail. The remaining coverage gap is therefore concentrated among lower-performing schools that are least likely to participate at all, rather than among high-performing schools that the program has not yet reached. As we saw in the previous sub-section, middle performing schools are likely to have a fair number of top talent, and therefore expansion and retention in this middle could have an impact on the total top talent identified in the country.

But although it seems to intuitively matter, does this form of expansion actually matter for identifying top talent? To answer this we consider a counterfactual question: if we ranked every school in the country from most to least predicted top talent, how much total talent would be identified as the national competition progressively includes different groups of schools?

A predictive model is used to estimate the number of students in each school that didn't participate, but that would be expected to advance from Round 1 to Round 2 (R2Qs) in 2025, based on observable school characteristics. Specifically, we estimate an ordinary least squares regression using only schools that participated in the RMO during 2023–2024, with the number of Round 1 advancers as the dependent variable. Predictors include standardized national examination (OLNE) performance, lower secondary enrollment, rural location, internet availability, science-school designation, school governance type, and district fixed effects. The estimated coefficients are then applied to all schools in the 2025 dataset—including both participating and non-participating schools—to generate predicted numbers of Round 1 advancers.

Figure 4 shows what happens when we rank all schools from highest to lowest predicted number of strong students (R2Qs) and then add the top talent students up one by one. As we move down this ranked list, the cumulative total shows how much predicted talent we have captured so far.

We then separate this accumulation by participation group. The black dashed line shows what

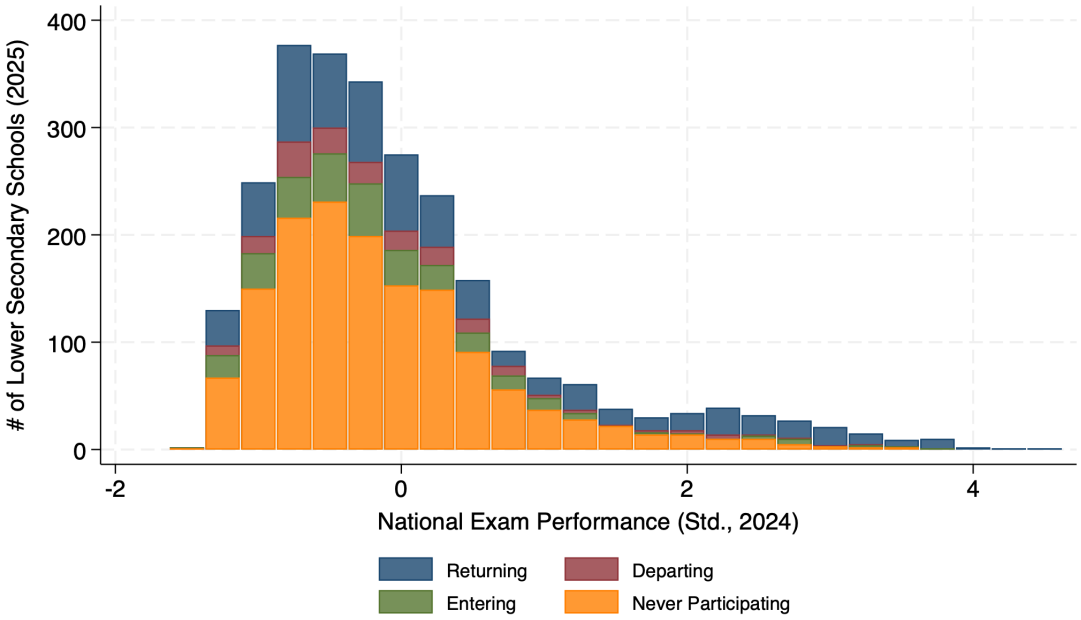


Figure 3: This figure shows the distribution of lower secondary schools by national exam performance and participation trajectory in 2025. Each bar represents the number of schools in a 0.25 standard deviation bin of school-average OLNE performance. Schools are classified into four mutually exclusive categories based on their Round 1 participation status in 2024 and 2025: *Returning* (both years), *Departing* (2024 only), *Entering* (2025 only), and *Never Participating* (neither year). Bars are stacked with Never Participating at the base.

total top talent captured looks like if we include every school. The lines for Returning, Entering, and Never Participating schools show how much each group contributes to that total as we move through the ranking, with bold lines representing the actual talent and dashed lines representing predicted talent. The key pattern is that Never Participating schools contribute a large and steadily growing share of total predicted talent, especially because there are many of them spread throughout the distribution, not just at the bottom. As a result, the gap between participating schools and the full population keeps widening as we move down the ranking, showing that missing talent is not concentrated in a small set of obvious schools, but is instead spread broadly across many schools that are not currently in the program. In terms of number of missing talented individuals, we estimate that if every Never Participating school was reached, we would identify around 16,000 more R2Qs.

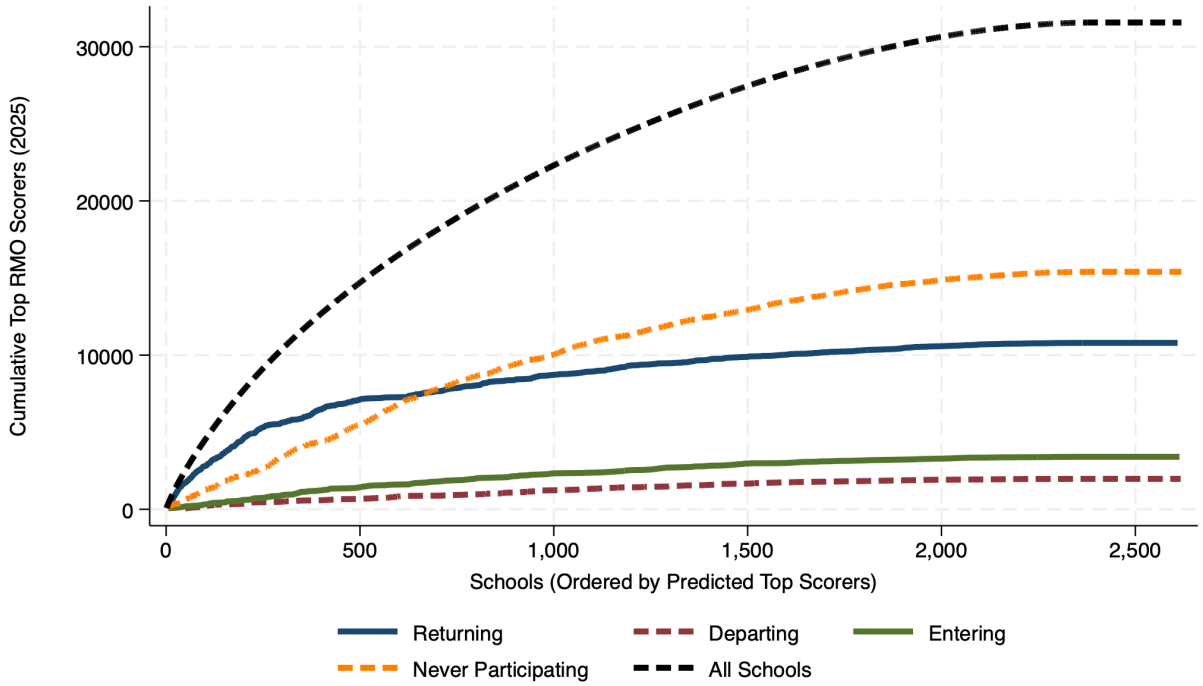


Figure 4: This figure shows cumulative R2Qs (actual and predicted) by school and participation trajectory in 2025. Schools are sorted from highest to lowest R2Q count and cumulative R2Qs are plotted for each participation category and for all schools combined. The gap between the *All Schools* line and the sum of the *Returning* and *Entering* lines represents predicted talent in schools not currently participating in the JRMO. Categories are defined as in Figure 3.

5 Discussion

In this paper, we explore how national talent search institutions identify potentially highly talented individuals, especially in hard-to-reach contexts such as in many low- and middle-income

countries (LMICs). We investigate this in the context of the recently formed Rwandan Mathematics Olympiad (RMO). While the RMO has expanded from its small pilot in 2019 to include over 900 schools by 2025, a large proportion of Rwandan schools still do not participate in the competition, potentially resulting in missing top talent in these schools. We document a strong relationship between school performance in the national exams and both their participation in the RMO, and the likelihood that they have high performing students in the RMO. As the RMO has expanded it has reached more middle performing schools, but still 'misses' a large fraction of potential high performers in the competition. What if these are potential Fields medal winners who are lacking an opportunity to be discovered and nurtured at a young age?

Our findings suggest that expanding national Olympiad systems substantially broadens access to mathematical competitions, but does not eliminate inequalities in who is discovered. Rather than identifying talent directly, Olympiad systems rely on schools, teachers, and local institutional capacity to bring students into the pipeline. As a result, the search process reflects variation in school participation as much as variation in underlying ability. Talent-search institutions therefore reduce one layer of inequality while simultaneously creating another.

Our findings have implications for governments and organizations that are increasingly investing in programs designed to identify and develop high-potential individuals, recognizing that innovation and long-run economic growth depend on cultivating exceptional talent. Our findings suggest that understanding who is identified is as important as understanding how identified individuals are subsequently developed. More broadly, the paper highlights the role of institutions in transforming latent ability into realized human capital, shaping who ultimately enters the pipeline to become scientists, inventors, and other knowledge producers.

We are looking forward to several next steps with this project. First, we have access to Ministry of Education data on teachers in schools. By matching participating students with their teacher, we hope to identify teacher characteristics that predict participation and success in the JRMO. Second, we are designing a randomized controlled trial that will introduce interventions aimed at increasing teacher engagement in the Rwanda Mathematics Olympiad (RMO). These interventions will be grounded in mechanisms identified from the descriptive data analysis and qualitative interviews conducted in Rwanda, including information frictions, weak incentives, and limited support for teachers.

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