Early Mentors for Exceptional Students*

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Abstract

Although we are acquainted anecdotally with extraordinarily people like Mozart and Marie Curie, there is little systematic research on how children with exceptional ability develop into truly extraordinary talents. Is the supply of extraordinary talent inelastic, dependent on a rare combination of innate gifts and the availability of mentors who are themselves world-class (Irène Joliot-Curie and her mother Marie)? Or, could the supply be fairly elastic because mentors need only have abilities within the normal range? I analyze these questions in the context of mathematics, where there is a consensus on how exceptional ability presents itself in children. I show that mathematics teachers who organize clubs and competitions can identify and foster exceptional math students, causing them to win honors, attend selective universities, major in STEM fields, and have careers in which they disproportionately spur economic growth. I demonstrate that there are many exceptional math students without mentors who could be reached with modest investments.

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1 Introduction

The biographies of extraordinary musicians, athletes, and scientists often reveal paths shaped by early demonstrations of innate ability and the significant influence of childhood mentors. These accounts suggest that the supply of exceptional talent depends not only on innate ability but also on access to capable mentors. While previous research suggests that early mentors are key to developing extraordinary talent, there is a lack of causal evidence from observable non-parental mentor-mentee relationships. This evidence is essential for understanding the elasticity of extraordinary talent (Ellison and Swanson, 2016; Bell et al., 2019; Hoisl, Kongsted and Mariani, 2023; Airoldi and Moser, 2024).

I consider two hypotheses for the types of early mentors required for the production of extraordinary talent. One hypothesis, which I call the "expert mentor" hypothesis, posits that extraordinary talent arises when a child with exceptional abilities is paired with a mentor who also possesses incredible talent. Under this hypothesis, the supply of extraordinary talent is largely inelastic, as both the mentee and mentor must be exceptional. The "proficient mentor" hypothesis posits that a reasonably capable mentor who can identify and nurture the abilities of exceptional children may suffice. If this were true, the supply of extraordinary talent could be more elastic, depending on the availability of mentors in educational or social settings. In the case of extraordinary knowledge producers, this would have important implications for scientific progress and economic growth (Rosen, 1981; Romer, 1990; Azoulay, Graff Zivin and Wang, 2010; McHale et al., 2023).

In my paper I test the proficient mentor hypothesis in the context of mathematics by estimating the *causal* effect of making proficient mentors available to exceptional students. Mathematics is a natural domain to test this hypothesis for a few reasons. First, there is a large, decentralized supply of potential proficient mentors with access to potential mentees–math teachers. Second, there is a general consensus on how exceptional math ability presents itself in childhood (i.e. advanced problem solving). Lastly, exceptional math students often pursue careers in science, technology, and innovation where they can generate significant positive externalities.

I estimate the causal effects proficient math mentors have on schools and exceptional math students. By leveraging exogenous variation in the arrival or activation of math mentors at schools, I provide causal evidence that math mentors help reveal and develop exceptional math talent. In a separate analysis leveraging differential access to potential math mentors, I estimate the impact these mentors have on the later-in-life outcomes of students. My causal estimates (LATE) imply these mentors greatly increase the probability exceptional math students attend highly-selective universities, major in STEM, earn PhDs, and pursue research careers. I then estimate the amount of exceptional math talent at schools without such mentors. Using my estimated mentor effects, I provide back-of-the-envelope estimates for how providing these students with mentors would increase the number of students with these outcomes.

This research leverages novel data from math competitions including the American Mathematics Competitions (AMC) and Math League to identify exceptional math students and math mentors. These math competition data are combined with data from online professional profiles to determine the later-in-life outcomes of students and retrieve additional information on mentors.

The AMC has been dedicated to identifying exceptional math talent in youth since 1950, and I use data from their competitions for the same purpose in this paper. The AMC has long published national summaries of its middle school and high school competitions, recognizing top performing students in various honor roll lists (Committee on the American Mathematics Competitions, 1980–2023). These lists, available since 2010 online and earlier in printed booklets, contain detailed information on thousands of exceptional math students each year, including their competition scores, school, city, and state. To extend the dataset back to 1980, I tracked down copies of these booklets by contacting thousands of current and former math teachers and digitized the data. There is, however, effectively no information on the teachers who organized these AMC competitions at their schools. This is where the Math League data is critical. Administrative data from Math League allow me to identify individuals–overwhelmingly math teachers–who organized math competitions at thousands of different middle schools and high schools from 1994 to 2020. These individuals–who facilitate Math League, an extracurricular math activity designed for talented math students–are the math mentors in this paper.

By matching math mentors and AMC high scorers to their LinkedIn profiles, I am able to gather information on their education and work histories. For the math mentors, these data provide insights on who these mentors are. Are they above-average math teachers or exceptional individuals themselves? The descriptive evidence suggests they fall primarily into the earlier category: above-average math teachers. This is promising for the elasticity of great scientists and innovators; it suggests early mentor access could be scaled, with most schools already having a teacher who could be "activated." For the exceptional math students, I use these data to observe later-in-life outcomes of exceptional students that math mentors might influence like attending a selective university, majoring in a STEM, earning a PhD, and/or working as a scientist or researcher.

The matched AMC high scorer data allow me to provide novel descriptive evidence on the educational and occupational choices of exceptional math students. Much of this evidence would be impossible to produce with analogous data from standardized tests like the ACT/SAT because those tests censor the math abilities of these students (Ellison and Swanson, 2010). Indeed, this censoring issue may be why a handful of highly selective universities like MIT and Caltech request applicants list their AMC scorers if they have participated (Surjadi and Randazzo, 2024). Such schools cannot rely on the ACT/SAT to identify the next John Nash. With this in mind, I present three descriptive facts on these students:

- **Fact 1:** Exceptionally talented math students are disproportionately involved in science, innovation, and entrepreneurship.

- **Fact 2:** Even at the fair right tail of the math ability distribution, exceptional math students continue to sort by ability.
- **Fact 3:** Even after controlling for ability, there are significant demographic gaps in those that attend selective universities and pursue science.

The first and second facts highlight the role exceptional math students in science and research, which underscores the motivation for studying the early mentors of these students (i.e. potential to generate positive externalities). The third fact highlights that even among the most exceptional math students in the US, there are still substantial gaps in educational and occupational outcomes.

By leveraging plausibly exogenous variation in the timing schools begin participating in Math League, I find that math mentors play a crucial role in identifying exceptional math students at their schools. Specifically, when a math mentor becomes active at a middle school, the number of top AMC scorers at that school increases dramatically–by 165%. For high schools this effect is smaller, but still large (47%). Various tests suggest that these effects result from the efforts of the math mentors, who expand access to competitions, encourage participation, and provide preparation and training. While it may seem unsurprising that increased investment in math competitions leads to greater success, the key implication is that, without a dedicated math mentor, many exceptional students may go unidentified by the AMC and, more importantly, may lack the mentorship necessary to develop their unique abilities. Given the decline in extracurricular math activities (Figure 1), the US may be less effective at both identifying and nurturing exceptional talent at the school level than it has been in the past.

I provide causal evidence that the effects of high school math mentors on exceptional math students are large. This analysis relies on a sample of middle school top AMC scorers, students who have already demonstrated they are exceptional in mathematics prior to high school. First, I provide OLS estimates that suggest having a math mentor in high school increases the probability of attending a highly-selective university (5.7pp), majoring in STEM (3.8pp), earning a PhD (2.2pp), and pursuing a career as a scientist or professor (1.7pp). These estimates include middle school fixed effects and a measure of middle school math ability (national middle school AMC rank). Recognizing these OLS estimates may be biased, I estimate these mentor effects using an instrumental variables strategy. My instrument is whether the student's middle school is within five miles of a high school in the same district with an active math mentor. The IV estimates are significant and notably larger–though less precise. These IV estimates correspond to the local average treatment effect (LATE) and imply mentor effects are particularly large for students whose mentor status is conditional on mentor availability. In the case of attending a highly-selective university, the IV estimates imply mentors increase the probability by 41pp.

To better understand the amount of exceptional math talent in the US, I estimate the number of exceptional math students at a large set of public high schools without a math mentor. These “missing” exceptional math students are the students who were *not* identified by the AMC because their school did *not* participate. My estimates indicate that around 36% of the exceptional math students who would participate and excel in this activity are not being identified because they lack a mentor who facilitates the activity. These “missing” students are disproportionately from states with large rural populations, suggesting inequalities in access to resources relevant to these students may be related to population concentration. From the perspective of a small community this is reasonable: why should a city allocate even a small amount of resources for a student type that only appears once every ten years? Aggregating to the national perspective provides an answer: because students of this type might generate large positive externalities.

I use results from the aforementioned analyses to provided back-of-the-envelope estimates for the impact of providing broader access to math mentors. These estimates suggest expanding access to math mentors at these schools would dramatically increase the number of exceptional math students who attends selective universities, major in STEM, earn PhDs, and pursue careers as scientists or professors. Based on the descriptive evidence on mentors and the modest costs of these activities, it seems expanding access in this way is, indeed, feasible and relatively low-cost given the potential positive externalities these students could generate.

In summary, my paper makes four key contributions to understanding the role of early mentors in the production of knowledge creators. First, I provide causal evidence that school-based mentors play a critical role in identifying and developing exceptional math students, who often go on to become scientists and innovators. Second, I demonstrate that these mentors significantly influence students’ long-term trajectories, increasing the likelihood they become knowledge producers. Third, I show that many exceptional students remain unidentified, particularly in geographically disadvantaged areas, highlighting inequities in talent identification. Finally, I introduce several large, novel datasets that offer valuable opportunities for future research in this field.

1.1 Related Literature

This research contributes to the literature on how childhood characteristics and environment influence later-in-life knowledge production. Previous studies show that high mathematical ability in childhood strongly correlates with knowledge production in adulthood (Aghion et al., 2017; Akcigit, Grigsby and Nicholas, 2017; Bell et al., 2019; Agarwal and Gaule, 2020; Morgan et al., 2022). At the same time, this literature highlights the importance of environmental factors—such as exposure to innovators, neighborhood characteristics, and parental income, education, occupation—in determining who becomes an inventor or knowledge producer later in life (Morgan et al., 2022; Hoisl, Kongsted and Mariani, 2023; Airoldi and Moser, 2024). My paper advances this literature in two important ways. First, I provide causal evidence for a mechanism hypothesized in this literature by directly linking exceptionally talented math students to non-parental mentors who are not themselves field experts. Second, I introduce a large, novel data set of exceptionally talented math students from diverse backgrounds that can be used in further research in this literature.

This research contributes to the related literature on the college choices of high-achieving students. This research provides evidence that information inequalities prevent some high-achieving students from applying to and/or attending selective universities (Bettinger et al., 2012; Hoxby and Avery, 2014; Falk, Kosse and Pinger, 2020; Dynarski et al., 2021). Hoxby and Avery link these information gaps to limited access to mentors who have attended such universities. I make two contributions to this literature. First, I provide descriptive evidence that gaps in selective university attendance persist even among students whose talents exceed what can be measured by the ACT/SAT. Second, I provide causal evidence that school-based mentors can greatly increase the probability high-achieving students attend selective universities.

My research also contributes to the literature in economics and developmental psychology that examines the impact of natural mentors on children's development (Zimmerman, Bingenheimer and Behrendt, 2005; Miranda-Chan et al., 2016; Van Dam et al., 2018; Hagler and Rhodes, 2018; Kraft, Bolves and Hurd, 2023). My work builds on this literature, particularly the research of Kraft et al., who study school-based natural mentors (teachers, counselors, and coaches) and find that these mentors increase college attendance by 9.4 percentage points, with the largest effects observed among students from lower socioeconomic backgrounds (Kraft, Bolves and Hurd, 2023). My primary contribution to this literature is evidence that there are positive natural mentors even for students at the far right tail of ability.

2 Mentors in the Production of Exceptional Talent

To distinguish between the expert mentor hypothesis and the proficient mentor hypothesis, and to understand their implications for the production of talent, consider a simple model of the production of aggregate talent in a given field. Let T represent the aggregate stock of exceptional talent. The production of this talent is a transformation process where children with exceptional ability are shaped through exposure to mentors, who may either be experts or proficient in the field.

To demonstrate how mentors contribute to the production of talent under the two hypotheses, I consider a stylized Cobb-Douglas talent production function where talent T is produced with fixed technology A through the combination of the supply of children demonstrating exceptional ability in the field (C) and the number of expert (e) and proficient (p) mentors. I express the latter mentor quantities as the product of the number of individuals with expertise and proficiency in a given field (N_e and N_p, respectively) and the shares of these individuals who serve as mentors (p_e and p_p, respectively):

$$T = AC^{\alpha}(p_p N_p)^{\beta}(p_e N_e)^{\gamma} \tag{1}$$

where because expertise is scarce, $N_e << N_p$, and because expertise is more valuable in the production of talent, $\gamma > \beta$. Taking society's endowment of raw talent C and potential mentors N_e and N_p as fixed, the extent to which T can be increased depends on p_e, p_p, and the elasticities in the production function.

Under the expert mentor hypothesis, proficient mentors are unable to influence the production of exceptional talent. In the production function, this hypothesis implies $\beta = 0$. In this case, T can only be increased by increasing the number of expert mentors. Even if the elasticity γ is large, this pathway faces critical limitations in its ability to increase T. First, to the extent that the supply of experts in any given field is limited, the number of potential expert mentors is capped and far less than the number of potential mentors. Second, by virtue of the scarcity of expertise, shifting experts into mentorship roles may be costly, both socially through taking them away from their domains of expertise and privately from their inability to capture the returns to their expertise.

Alternatively, under the proficient mentor hypothesis, $\beta > 0$, and mentors who are not themselves experts can influence T. These proficient mentors serve as substitutes for expert mentors in the production of exceptional talent. Although expert mentors are more productive in cultivating talent, their scarcity and the opportunity cost of diverting them from their fields of expertise create trade-offs. In fields where the scarcity of such mentors is very high or the opportunity cost of diverting these mentors is high, proficient mentors, although less productive, become viable substitutes.

To test whether the expert or proficient mentor hypothesis holds true, I estimate the effects of proficient mentors on the outcomes of children with exceptional ability. The expert mentor hypothesis would predict that proficient mentors do not influence the outcomes of children with exceptional ability, whereas the proficient mentor hypothesis would predict that exposure to a proficient mentor can positively impact the outcomes of children with exceptional ability.

3 Data

For this paper, I require a large, geographically and temporally diverse sample of exceptional math students, along with information about their middle schools, high schools, math mentors, and later-in-life outcomes. Consequently, this research makes use of a variety of data sources. This section provides a brief overview of the data used in this paper including data from the American Mathematics Competitions (AMC), Math League, LinkedIn, the National Center for Education Statistics data (NCES), and the Wisconsin All Staff Reports,

3.1 American Mathematics Competitions (AMC) Data

I constructed a novel dataset of exceptional math students by compiling AMC results from 1980 to 2020. Results from 2011 to 2020 were collected from the AMC digital archive, while results from 1980 to 2010 were hand-collected from physical books, which were distributed annually to participating schools. I gathered these books by contacting thousands of current and former math teachers, which I then digitized.

While the data cover various AMC competitions, this paper uses the from the flagship middle school competition (AMC 8) and flagship high school competitions (AMC 10 A/B and AMC 12 A/B).[12] The data contain both summary statistics for these competitions and various lists of high-scoring students. The summary statistics provide details on the number of participants and schools, score distributions, and commentary. The student lists include each top scorer's first initial, last name, score, grade, school, city, and state. In total, the middle school observations exceed 300,000 (AMC 8), while the high school observations exceed 500,000 (AMC 10/12) .

For each student listed, I calculate their rank in the given competition based on their score. This serves as my measure of student math ability.[3] In most years, scoring in the top 3,200 is sufficient to make the student honor roll lists (Figure 2). I leverage this threshold for a school-level outcome in my analyses.

3.2 Math League Data

One limitation of the AMC data is the lack of a complete list of participating schools. While I can infer some participation from the honoree lists, I cannot determine if schools with no honorees failed to participate or simply lacked top-performing students. This uncertainty limits the data's ability to fully capture the distribution of math talent across US schools.

For this reason, I also collected data from Math League, which has organized math competitions throughout the US at the elementary, middle, and high school level since 1977. These Math League data span 1994 to 2020, and they include information on all participating schools, the individuals at these schools who facilitate these competitions, and the names of top-performing students.

These data are critical for my analyses for a variety of reasons. First, they allow me to determine the set of schools participating in the competition over time. This is in contrast to the AMC data, where I cannot accurately determine participation. Knowing exactly when these competitions are offered is necessary for my later empirical strategies because they allow me to determine when a

[1]The data also cover the American Invitational Mathematics Examination (AIME) and the United States American Mathematical Olympiad (USAMO).

[2]The AMC has changed the names of these competitions over the years. From its inception in 1985 until 1999, AMC 8 was called the American Junior High School Mathematics Examination (AJHSME). Before 2000, there was only one high school competition. From 1950 till 1972 this competition was simply called the Annual High School Contest. From 1973 till 1982, this exam was called the Annual High School Mathematics Examination, which slightly change to the American High School Mathematics Examination for years 1983 to 1999. In 2000, the AMC separated the competition into the AMC 10 and AMC 12, which targeted 9th/10th graders and 11th/12th graders respectively. Finally, in 2001 the AMC began offering two different dates for the AMC 10 and AMC 12 resulting in the A and B distinction.

[3]Raw score is problematic because the competition questions vary in difficulty over time. Score percentile is also problematic because the number of participating schools and students decreases dramatically over the sample period. Score rank suffers from the same problem, but to a lesser extent; the score rank of top-performing students is unaffected by the number of low-performing students, while their score percentile is affected by such students.

math mentor is active at a school. Second, the information on the school employees who organize Math League at their schools–including full names and years active in Math League–provides key insights on who these mentors are when combined with other data sources. Lastly, the information on top-performing students allows me to observe some of the students participating in the activity. In one of my analyses, this information enables me to distinguish between exceptional math students who do and do not participate in the program.

3.3 LinkedIn Data

I use data from Revelio Labs, which contains online professional profiles of over 700 million individuals, to track the later-in-life outcomes of students in the AMC sample. From these profiles, I observe names, employment history, educational backgrounds, and self-reported information on jobs and universities. Revelio Labs also imputes gender and race based on names and location, which are used throughout my analysis.

I match AMC students to LinkedIn profiles by first matching on initials, last name, and graduation years, and then using fuzzy matching based on high schools when available. I further refine matches using a logit model to predict the likelihood of an accurate first-name match, restricting the final sample to those with a high predicted probability.

The outcomes of interest include four binary variables reflecting common milestones for highly productive scientists and researchers: attending a highly selective university, majoring in a STEM field, earning a PhD, and working as a scientist or professor.

3.4 Supplementary Education Data

I collected data on public and private schools across the US through the National Center for Education Statistics (NCES). The data for public schools come from the Common Core of Data (CCD), which provides annual records for all public schools extending back to 1986. The data for private schools come from the Private School Universe Survey (PSS), which provides biennial records for most private schools extending back to 1989.[4]

The CCD and PSS data provide information on school names, geographic locations, grades offered, student enrollment and demographic counts, and faculty employment[5]. Based on the school identifying codes, the CCD data from 1986 to 2020 include 160,760 unique public schools, of which 43,904 offer 12th grade. On the private school side, the PSS data from 1989 to 2020 include 80,497 private schools with 21,766 ever offering 12th grade. I match the schools in the AMC and Math

[4]Per the PSS, "The survey universe is composed of schools from several sources. The main source is a list frame, initially developed for the 1989-90 survey. The list is updated periodically by matching it with lists provided by nationwide private school associations, state departments of education, and other national private school guides and sources. Additionally, an area frame search is conducted by the Bureau of the Census."

[5]For private school data in odd number years, I simply use PSS data from the previous even number year.

League data to these sources using school names and location information. The NCES data provides important information on the environments of the Math League schools and schools of top AMC students. Critically, the NCES data also allow me to determine the set of schools each year with *no* top AMC student and the schools *not* participating in Math League.

I also use data from the NCES School Attendance Boundary Survey (SABS), which provides the 2015-2016 attendance boundaries for over 70,000 schools in 12,000 districts across the US. This data enables me to more accurately and precisely identify which middle schools feed into which high schools, compared to relying on the relative distance between schools. This accuracy and precision is important for my instrumental variables strategy.

The final data I use for this paper comes from the Wisconsin All Staff Report, which provides detailed information on staff assignments in Wisconsin schools from 1995 to 2024. I use these data to obtain more detailed descriptive evidence on a subsample of Math League mentors. These data allow me to better understand the positions of these mentors, their teaching experience, and the timing of them becoming Math League mentors.

4 Descriptive Evidence on Math Mentors and Math Talent

In this section, I present a series of descriptive findings on the distribution of top AMC students across majors, colleges, and careers. These findings lead to three main takeaways: (1) exceptional math students are disproportionately involved in science, innovation, and entrepreneurship; (2) even at the fair right tail of the math ability distribution, exceptional math students continue to sort by ability; and (3) even after controlling for ability and secondary schooling, there are significant demographic gaps in attendance at selective universities and in the pursuit of science education and careers. These takeaways would be challenging to derive using data from common standardized tests like ACT/SAT because which often censor math ability beyond the 99th percentile.

4.1 Samples and Methods

The descriptive analysis in this section relies on two samples of high achieving math students, matched to their LinkedIn profiles. One sample consists of 14,249 students from the middle school AMC data; the other includes 24,424 students from the high school AMC data. In brief, I match on first initial, last name, and either high school or college graduation year, and then apply a logit model with additional information to estimate the probability that a potential match leads to an exact first name match. A detailed description of this process is provided in Appendix A.

To benchmark I construct a reference sample of US college graduates using the LinkedIn data for both AMC-matched samples. For each AMC student, I randomly select an online professional profile of a US college graduate from the same graduating cohort. These reference samples serve as benchmarks, allowing for comparison of career and educational outcomes while accounting for temporal variation in the AMC-matched samples. I could, instead, benchmark the AMC samples against data from the NCES, but my approach alleviates concerns with respect to selection onto LinkedIn.

Although the descriptive patterns and takeaways are largely consistent between the middle school and high school matched samples, there are distinct advantages to presenting both. The high school sample is larger, spans a longer time period, and includes exams such as the AMC 12, which have been studied by other researchers, providing additional context for the descriptive analysis (Ellison and Swanson, 2010, 2016, 2023). The middle school sample, however, also warrants inclusion. It offers insights from a previously unexplored data source and is essential for a key empirical strategy later in the paper, where the high school sample would not serve as a substitute. For brevity, when reporting analogous statistics or referencing similar figures and tables for both samples, I use slashes to present the middle school and high school data side by side (e.g. 8%/10%).

4.2 Majors, Colleges, and Careers of Exceptional Math Students

Fact 1: Exceptionally talented math students are disproportionately involved in science, innovation, and entrepreneurship

AMC students attend highly-selective universities (22%/31%), major in STEM (48%/54%), earn doctoral degrees (8%/12%), and pursue careers as scientists or professor (8%/11%) at very high rates (Table 1). Compared to the matched sample of college graduates, they are ten times as likely to attend an elite undergraduate institution, twice as likely to major in STEM, five times more likely to earn a PhD, and three times more likely to pursue a research career. The primary demographic difference between the AMC samples and the reference samples is that the AMC sample has a higher share of Asian individuals.

The high shares of AMC students majoring in STEM, pursuing a PhD, and choosing careers in research obscures important heterogeneity in the fields pursued by these students. While they display exceptional ability in mathematics, they typically pursue fields outside of mathematics and statistics. Indeed, only 9%/14% of the sample major in mathematics, statistics, or actuarial sciences. Higher shares of these students major in engineering (19%/21%), computer science (12%/14%), and social science (16%/14%). Other common majors include the life sciences (8%/7%), physics/astronomy (3%/5%), and chemistry/biochemistry. Many of the students in these majors continue and earn a PhD and work as a professor or scientist (Table 2).

Ultimately, the economic and scientific impacts of these students depend on their career decisions and opportunities after college. From Table 1, it is clear these students pursue research careers at a relatively high rate, and the estimates in Table 3 suggest there continues to be sorting by math ability even amongst these top students. These statistics and estimates, however, fail to demonstrate the unique economic and scientific contributions of these students.

To better communicate the the role these students play in the economy, I perform a text analysis on the job titles and company names they list on their online professional profiles. I begin by compiling a list of all the unique words appearing in the job titles of matched AMC students. I then determine the frequency with which each of these words appears at least once in the job titles of those students in my AMC matched sample. I then count the frequency with which these words appear in the job titles of the individuals in my reference sample. This latter count helps me distinguish between words that are generally common in LinkedIn job titles and those that are relatively unique to AMC students. I make similar frequency counts for the company names listed on these profiles.

The text analysis reveals these AMC students pursue impressive careers in a diverse set of fields. It indicates top AMC students work in academia, science, technology[6], medicine, and finance at rates much higher than other college graduates (Table 4). The list of company names confirms these AMC high scorers are often employed by the most innovative and prestigious companies and universities in the world (Table 5).

Fact 2: Even at the fair right tail of the math ability distribution, exceptional math students continue to sort by ability.

Many of these AMC students have a mathematical ability that is censored by traditional pre-college measures like the ACT/SAT. Ellison and Swanson argue that an AMC score of 100 on the 2007 AMC 12 A (Rank 2,812) is roughly equivalent to a perfect SAT math score and also serves as a more reliable measure of ability. Yet, relative AMC performances continue to have predictive power beyond this range of ability for the probability students major in STEM, attend an elite undergraduate institution, earn doctoral degrees, and pursue research careers, researcher, or professor. These relationships persist even after controlling for student gender, race, high school graduation year, and school fixed effects (Figure 3 /4).

To estimate the association between these outcomes and AMC performance, I regress each outcome (y_i) on AMC rank ($rank_i$) while including controls for student gender, race, grade during observed AMC test, AMC test, hometown share of college graduates, high school graduation cohort fixed effects (τ_t), and school fixed effects (δ_s). I multiply the AMC ranks by 1,000 and make them negative, so the coefficient on $rank_i$ corresponds to an improvement in AMC rank by 1,000 positions.

$$y_i = \alpha + \beta rank_i + \gamma_t + \delta_s + X_i\lambda + \varepsilon_{ist} \tag{2}$$

[6]The frequency of *cofounder* in these job titles hints at the incredible impact some AMC high scorers have had in technology startups. While not all are included in these matched samples, Sergey Brin (Google), Mark Zuckerberg (Meta), Peter Thiel (PayPal), and Sam Altman (OpenAI) were all top AMC scorers (Committee on the American Mathematics Competitions, 1980–2023)

The models (Equation 2) are estimated using OLS for the four outcomes. The estimated coefficients are provided in Table 3. The omitted category is white, male students.

The estimates indicate a 1,000 rank improvement in AMC performance is associated with a 2.3pp/1.3pp higher probability of attending an selective university, a 1.5pp/1.6pp higher probability of majoring in STEM, a 0.7pp/1.3pp higher probability of earning a PhD, and a 0.5pp/0.4pp higher probability of becoming a scientist or professor. The estimates are all highly statistically significant. Compared to the relationship between these outcomes and hometown college share, the AMC rank coefficients are sizeable.

Fact 3: Even after controlling for ability, there are significant demographic gaps in those that attend selective universities and pursue science.

The estimates in Table 3 reveal that even after controlling for ability, there are numerous demographic gaps in these later-in-life outcomes. Gaps exist between male and female students and asian and non-asian students.

The gender gaps are the most striking. In the case of pursuing science, the estimated coefficients indicate exceptional female students pursue STEM majors at a rate that is 19pp/20pp lower than male students. While gender gaps in STEM have been well documented in previous research, finding this large a gap among exceptionally talented male and female students despite the rich set of controls is surprising. It is possible this gap is simply driven by gender differences in taste for STEM, but there is also a substantial gap in the rate these male and female students attend highly-selective colleges. Per the estimates, female students are 4pp/6pp less likely to attend a highly-selective colleges. This, in turn, may be influencing the share of these students who pursue PhDs, for which there is also a gender gap (0.9pp/2.1pp). There are also significant gaps between asian and non-asian exceptional math students for many of these outcomes, with asian students being more likely to attend selective universities and major in STEM.

4.3 Who Becomes a Math Mentor?

To provide descriptive evidence on the individuals who become Math League mentors at high schools, I match Math League mentors from the Math League data to the Wisconsin All Staff data (1995-2024) by first name, last name, year, and school. This results in 1,327 matched mentor-years associated with 329 unique mentors. Of these unique mentors, I can observe the first year for 257.

In Table 6, I provide information on the demographic characteristics, education, and work experience of these 257 individuals during their first year as mentors. Of these individuals, 91% are teachers with most others being dedicated gifted & talented coordinators. The vast majority of these teachers are mathematics teachers, though there are some computer science and physics teachers organizing the program as well. Effectively none of these mentors are principals, and only a small share are department chairs. In terms of experience, they are in their mid-careers with an average of 12 years of experience, a majority of this experience being within their current district. Nevertheless, a decent share (32%) are relatively recent hires, who first become Math League mentors during or before their third year in the district. Only a small share have their roles as “Club Advisors” documented in the staff data, which suggests most mentors are not being compensated or formally recognized for organizing this activity. Nevertheless, the average number of years I observe these mentors organize Math League is 3.5 years.

The descriptive evidence from Wisconsin suggests these potential mentors might be abundant. That is, there may be a math teacher at most schools who could serve such as a mentor in Math League or for a similar program. To provide further evidence of this, I match Math League mentors from the Math League data to their LinkedIn profiles. I match on first name, last name, and school.[7] I provide summary statistics for these mentors in Table 7. The most notable additional piece of evidence from this LinkedIn matched sample is the low share of mentors who list attending a selective university. This adds further credence to the abundance of math teachers who could be school-based mentors to exceptionally talented students.

5 Math Mentor Effects on Schools and Students

In this section, I estimate the causal impacts of math mentors on both the amount of exceptional math talent revealed at schools and later-in-life educational and career outcomes of individual exceptional math students. To estimate the effect on the amount of talent revealed at a school, I exploit temporal variation in the arrival of the first Math League mentor at a school. Using a difference-in-differences design, I estimate the causal effect of having a Math League mentor on a school’s likelihood of participating in the AMC and on the number of exceptional math students identified by the AMC. To estimate the effect of these mentors on individual students, I exploit variation in whether students have mentors for an IV strategy. Taken together, these analyses provide evidence that math mentors help reveal and nurture exceptional math talent at their schools.

5.1 School Impacts: Revealing Talent

I take a quasi-experimental approach to estimate the effect of math mentors on the amount of talent revealed at their schools. This approach leverages the arrival, or activation, of Math League mentors at schools across the US from 1994 to 2020 in a generalized difference-in-differences estimation strategy.

For this strategy, I focus on a sample of *entry* Math League schools—those that first had a Math League mentor between 1994 and 2020. I begin by identifying all public non-charter, non-magnet

[7] Individuals can list many current and previous positions on the LinkedIn profiles. I ensure at least one of these positions is at the school in the Math League data.

middle schools present in the NCES data every year from 1994 to 2020. I then restrict the sample to schools that first had an active Math League mentor during this period. This restriction is crucial for my identification strategy, as it limits the analysis to schools on the margin of having a Math League mentor, allowing me to observe their behavior both before and after the mentor.

In Table 8a, I compare the entry Math League sample to two other samples of public, non-charter, non-magnet middle schools present in the NCES data every year from 1994 to 2020. The first of these samples is the *never* Math League schools–the schools that did not offer Math League during this period. The other sample is the *early* Math League schools. This sample is the set that offered Math League before 1994. The juxtaposition of the sample averages for these three disjoint sets of schools communicates how the schools used for my empirical strategy–the entry Math League schools–fit in the wider context of US public middle schools. I replicate this sample construction for public, non-charter, non-magnet high schools. The summary statistics for the analogous three samples are provided in Table 8b. The comparisons between the middle school entry sample and the other two middle school samples are similar to those for high schools.

When compared to the never Math League samples, the schools in the entry Math League samples have slightly higher shares of white and asian students. These samples differ more dramatically along with respect to community characteristics. On average, the schools in the early Math League samples are located in more populous and wealthier cities, with higher shares of college graduates. To help address issues of generalizability, I control for community characteristics in several different ways. Generalizability is tested directly Section 6.

The outcome of interest here is the number of top AMC scorers a school produces in a given year, which is my measure of revealed exceptional math talent.[8] Models estimated using OLS for this outcome are necessarily misspecified as they can generate negative predicted counts. Additionally, these top AMC counts are heavily skewed; while some schools generate counts exceeding twenty top AMC scorers, the vast majority of schools have zero top scorers. For these reasons, Poisson and negative-binomial estimation are more appropriate in this context. These models treat the outcome as a count variable, inherently restricted to non-negative integer values, and are better suited to handle the skewness present in the data. I choose to estimate my models using the negative binomial because these counts exhibit high a degree of overdispersion.[9] The coefficients generated using negative binomial are given in log-odds.

With the analytical samples situated and my preferred estimation approach discussed, I outline my generalized difference-in-differences strategy for estimating the mentor effect. I regress the

[8] I pick 3,200 as threshold here because 3,200 is a sufficient rank to make the both the middle school and high school AMC honor rolls during this period. For the middle school analysis, this is the number of 6th, 7th, and 8th grade students in the top 3,200. For the high school analysis, this is the number of 11th and 12th grade students in the top 3,200.

[9] Ellison & Swanson also choose the negative binomial to model the number AMC 12 students with a score of 100 or greater found at schools. Just as in their case, I find a likelihood ratio test rejects the Poisson alternative for both the middle school and high school context (Ellison and Swanson, 2016). When testing robustness, I replicate the analyses with Poisson, which yield similar estimates.

number of top AMC scorers on an indicator for whether a school has an active Math League mentor, while controlling for year fixed effects, community controls (log city population, city college graduate share, city per capita income) based on the 2000 census, and time-varying school characteristics including as the log number of enrolled students, teacher-student ratio, the racial composition of the school (shares of Asian, White, Black, and Hispanic students), and the share of free-lunch eligible students:

$$talent_{st}^{(r)} = \alpha + \beta mentor_{st} + \tau_t + X_{st}\lambda + \varepsilon_{st}. \tag{3}$$

If identification holds, β captures the causal effect of a Math League mentor on the number of exceptional math students revealed at a school in log-odds. I omit school fixed effects in my preferred specification because the negative binomial drops schools for which top AMC counts are constant–in this case always 0–throughout the period. These schools make up more than 60% of both samples and I am particularly interested in the effect of these mentors at schools where top AMC scorers might be rare. I also estimate the model with school fixed effects for comparison.

For identification to hold, the key assumption is that in the absence of a Math League mentor, the treated schools would have followed parallel trends in the number of top AMC scorers compared to the control schools. This parallel trends assumption is crucial for the validity of the difference-in-differences approach and is supported by the inclusion of rich controls and fixed effects. These controls account for differences across schools, such as student demographics and community characteristics, which might otherwise confound the relationship between Math League participation and AMC performance.

To provide evidence that the parallel trends assumption holds, I recast my difference-in-differences specification as an event study.

$$talent_{st}^{(r)} = \alpha + \sum_{k=-26}^{26} \beta^{(entry,k)} I\left[t = k + T_s^{(entry)}\right] + \beta_0 attrition_{st} + \tau_t + X_{st}\lambda + \varepsilon_{st} \tag{4}$$

Instead of using a static indicator for whether a school has a Math League mentor in a given year, the event study includes indicators for whether a school year aligns with a given year relative to when the school first had a Math League mentor, denoted as $I\left[t = k + T_s^{(entry)}\right]$. Additionally, it includes an indicator for whether the school had a Math League mentor previously, but no longer does, denoted as $attrition_{st}$. Together, the coefficients $\beta^{(entry,k)}$ capture the trend in revealed talent before and after a school first has a Math League mentor, while controlling for whether the mentor remains active in the post-period. Flat trends during the pre-period would support the parallel trends assumption.

The estimates indicate that math mentors have a significant impact on the amount of exceptional math talent revealed at a school (Table 9 and Table 10). The estimated coefficients imply Math League mentors have an enormous impact on the amount of exceptional math talent discovered at schools. They indicate mentors increase the number of top AMC scorers at middle schools by 248%. The analogous implied mentor effect at the high school level is 110%.

In Figure 5, I show the event study estimates for the models with and without school fixed effects. The event studies for the specification without school fixed effects–which are estimated using a larger set of schools–demonstrate that the pre-trends in revealed talent are flat leading up to the arrival/activation of the Math League mentor at the school, and then sharply increase over the course of two years after which the trends stabilize. These events studies support the parallel trends assumption and provide evidence that the mentor effects on revealed talent are quickly realized rather than gradual. The event studies for the specifications with school fixed effects have the same pattern, though are noisier.

The mentor effect on revealed talent indicate there are exceptional math students in the US who *rely* on math mentors to reveal their talents. This effect encompasses various mechanisms through which a mentor may influence the success of these student. These mentors may help facilitate peer effects between enthusiastic math students, they may help refine students' abilities through coaching, expose them to advanced concepts outside a traditional math curriculum, or encourage participation in the AMC. The estimated mentor effect on revealed talent is simply the aggregation of these effects.

Disentangling these effects would help determine the most productive efforts of these mentors, which is important when one considers expanding access to resources like these mentors. If, for example, the mentor effects on revealed talent are being entirely driven by expanding access to the AMC, then making the AMC universal would reveal all the missing exceptional math students with the only cost being the competition administration. The empirical challenge here is that I do not observe school participation in the AMC from year to year.[10]

This is directly connected to a key feature of the top AMC counts: they include zero counts drawn from two different distributions. Some of the zeros are *structural*; the school has no top AMC scorers because the school does not participate in the AMC. The other zeros are *random*; the school participates in the AMC, but does not produce any top scorers. Structural zeros are drawn from a Bernoulli distribution, while random zeros arise from a count distribution like the negative binomial distribution. Given these two types of zeros, a zero-inflated negative binomial (ZINB) approach may be more appropriate than the original negative binomial strategies. ZINB estimation also generates separate estimates for the mentor effect on AMC participation and on revealed talent conditional on participation.

I now briefly explain how the (ZINB) model functions in this context. For school s in year t, this model makes two predictions prior to predicting the number of top AMC 12 scorers, $\widehat{talent}_{st}^{(r)}$. One of these predictions is the probability that school s in year t does *not* participate in the AMC, $\hat{p}_{st}^{inf}$. This is estimated using the *inflate* part of the model. The other prediction this model makes is how

[10] AMC participation can only be confirmed for schools that have *at least one* top scorer.

many top AMC 12 scorers school s in year t would produce if the school *does* participate in the the competition, $\widehat{talent}_{st}$. This is estimated using the *count* part of the model. The predicted number of top AMC scorers is then the product of the non-participation probability and the talent estimate:

$$\widehat{talent}_{st}^{(r)} = (1 - \hat{p}_{st}^{inf})\widehat{talent}_{st}. \tag{5}$$

This approach allows me to separate the impact of Math League mentors on expanding access to the AMC, $\hat{p}_{st}^{inf}$, from their impact on the talent pool at a school $\widehat{talent}_{st}$.

With this in mind, I estimate Equation 3 using a ZINB model. I exclude school fixed effects because schools that never participate in the AMC would otherwise be dropped from the estimation. These schools are essential for estimating the mentor effect on expanding AMC access. Aside from the school fixed effects, I include the same controls for both the inflate and count portions of the model.

Per the ZINB estimates, Math League mentors increase the amount of talent revealed at a school by both increasing the probability schools participate in the AMC and, separately, increasing the amount of actual talent (Table 11). The latter estimates are very similar to the negative binomial estimates with school fixed effects. The coefficients from the inflate portion of the estimated ZINB models imply Math League mentors *decrease* the probability a school *does not* participate in the AMC by 72% for middle schools and 58% for high schools. The coefficients from the count portion of the models imply these mentors increase the amount of exceptional math talent by 18% at middle schools and 52% for high schools. I note that while the count estimates encompass a variety of mechanisms through which mentors impact exceptional talent, the inflate estimates capture the specific impact of these mentors on increasing school participation in the AMC. The event studies for these estimates are noisier, particularly for the count portion of the model (Figure 6).

The large estimated effects for the inflate portion of the model imply a significant share of the "missing" exceptional math students could be revealed by simply offering the AMC at more schools. From a policy perspective, this would certainly be easier than expanding access to mentors. Students identified through such an expansion would still receive credible signals of their ability. These signals could help them gain access to out-of-school enrichment programs while still in secondary school, improve their probability of being admitted to a selective university, or simply encourage them to continue pursuing math and education more generally. Students revealed in this way would, however, not benefit from other potential mentor effects (e.g. increased STEM enthusiasm from interactions with invested adult).

A deeper discussion of the mechanisms through which mentors influence the amount of revealed talent at a school is offered in Appendix A.

5.1.1 Robustness

To test whether the mentor effect estimates are being driven by advantaged or disadvantaged schools, I perform a heterogeneity analysis where I interact the indicator for Math League mentor, $mentor_{st}$, with the share of free-lunch eligible students at the school during the year fle_{st}:

$$talent_{st}^{(r)} = \alpha + \beta_0 mentor_{st} + \beta_1 fle_{st} + \beta_2 mentor_{st} \times fle_{st} + \tau_t + \pi_s + X_{st}\lambda + \varepsilon_{st}. \qquad (6)$$

The model is otherwise identical to Equation 3.

The estimates indicate the mentor effects are actually larger for more disadvantaged schools (Table 12 and Table B.1). The estimates from the negative binomial model with school fixed effects indicate that relative to a middle school with no free lunch eligible students, the mentor effect at a middle school where 20% of the students are free lunch eligible is 25.8% larger. The same holds for the high school estimates. Why might this be? One potential explanation for these differential effects is that these math mentors might be more likely to first *introduce* the AMC to more disadvantaged schools, while more advantaged schools were more likely to be participating during the preperiod. Another possibility is that exceptional students at disadvantaged schools may be less likely to be challenged by their schools' math curricula and math mentors compensate for this disadvantage. It may also be true that the math mentors at disadvantaged school are more motivated than their peers at advantaged schools–they may have to overcome more institution barriers to organize such programs–and those in the sample are particularly talented at revealing and fostering talent.

To provide evidence that these results are not being driven by misspecification, I repeat the analysis using OLS, Poisson, and zero-inflated Poisson (ZIP). The estimated mentor effects for these models are provided in Tables B.2 and B.3. The original results hold and those generated using Poisson and ZIP are similar in magnitude to the original negative binomial and ZINB estimates. The analogous event studies support the parallel trends assumption as before (Figure B.1). The results are robust to misspecification.

To further assess the robustness of my results, I conduct a placebo test using the never Math League sample. For this exercise, I randomly assign the sequences of Math League mentor variables, $mentor_{st}$, from a school in the entry sample to each school in the never Math League sample and estimate the mentor effects again using the negative binomial and ZINB. This provides two important checks. First, it checks that the effects are not being driven by unobservable trends in Math League adoption or math competitions more generally. If, for example, Math League adoption was correlated with a decline in the difficulty of being a top AMC scorer, the estimates produced by this placebo test would still be positive and significant. Why? The never Math League schools that do participate in the AMC would also experience an increase in top AMC scorers around the same Math League adoption years. Second, it allows me to check whether the coefficients on the covariates in the never Math League sample are similar to those in the original entry Math League sample. If these covariate coefficients differed greatly, it would cast doubt on the external validity of these models and the robustness of the specifications more generally.

This placebo test supports my identification strategy and specification. The estimated mentor effects are small and statistically insignificant (Table B.4 and Table B.5). This result suggests that the original estimates of the effect of Math League participation on the number of top AMC scorers are unlikely to be driven by spurious or uncontrolled time trends. Additionally, the estimated coefficients on the covariates are comparable to the original covariates. This serves as further evidence that my model is not mispecified and boosts the claim that the model is externally valid.

5.2 Student Impacts: Influencing Later-in-Life Outcomes

In this section, I estimate the causal effect of a high school math mentor on the later-in-life education and occupation outcomes of students who have already demonstrated exceptional math ability in middle school. To estimate these effects, I rely on a quasi-experimental design that leverages variation in student exposure to a potential math mentor. The sample used for this analysis is a subsample of the middle school AMC matched sample described in Section 4. In this case, the sample is restricted to those students who attended a public, non-charter, non-magnet middle school and who graduated high school in 1998 or later[11].

It is important to highlight several key characteristics shared by all the students in this sample. Every student included in this sample: (1) attended a public, non-charter, non-magnet middle school with a teacher/mentor who organized the AMC; (2) participated in the AMC 8; and (3) were recognized by the AMC for their exceptional math ability. Consequently, differences in the later-in-life outcomes of these students are not driven by differences along these dimensions.

I use the Math League data to determine which of these students have a high school Math League mentor. Ideally, I would observe which of these students participated in high school Math League, but I do not observe student participation. I do, however, observe the names of students who achieved a perfect score on at least one of the six Math League exams offered during a year. For this specific set of students, achieving at least one perfect score on one of the potentially twenty-four Math League exams available to them in high school should be relatively easy. Consequently, this serves a good proxy for Math League participation. Given this, I consider a student in my sample to have a high school Math League mentor if they achieved at least one perfect Math League score.

Not all students in this sample have the same potential to have a Math League mentor. While every student in this sample attended a middle school that offered the AMC 8, there is variation in whether these middle schools feed into a high school with an active Math League mentor. To capture this variation I construct an indicator for whether the students middle school was within 5

[11]Based on the grade reported in the AMC data.

miles of a high school that offered Math League during the years the student was in high school.[12]

I compare students who do and do not have a high school Math League mentor in Table 13. Pre-high school characteristics, such as middle school AMC performance and demographics, are fairly similar for students that do and do not have a Math League mentor. Unsurprisingly, the students who have a high school math mentor attended a middle school within five miles of a high school with an active Math League mentor. There are substantial differences in high school and later-in-life outcomes for these students, however. Those with a mentor are much more likely to attend a selective university, major in STEM, earn a PhD, and pursue a research career.

To estimate the impact of a high school math mentor on exceptional math students, I regress these outcomes on whether the student has a high school math mentor ($mentor_i$), while controlling for a rich set of student, school, and community variables, as well as year (τ_t), and location fixed effects (σ_s).

$$y_i = \alpha + \beta mentor_{ist} + \gamma rank_i^{(MS)} + \tau_t + \sigma_s + X_{ist}\lambda + \varepsilon_{ist}. \tag{7}$$

The student controls include a measure of pre-high school math ability (AMC 8 rank), high school graduation cohort, race, and gender. School-level controls, which are tied to the student's middle school during the AMC 8 observation year, include the log of total 6th, 7th, and 8th grade enrollment, student-teacher ratio, racial composition, and share of students that are free lunch eligible. Community characteristics including per capita income and the share of college graduates within the middle school's city (measured in the year 2000), are also included. For one set of estimates I use school district fixed effects, while for another I use school fixed effects. These help control for unobservable time-invariant differences in school district and school characteristics (e.g. education quality and STEM focus of community).

I use ordinary least squares (OLS) regression to estimate Equation 7 for various outcomes of interest. My results suggest the effects of math mentors on exceptional math students are substantial (Table 14). The estimates from the specification using district fixed effects, suggest math mentors increase the probability these students become high school top AMC scorers (15.5pp), attend highly-selective colleges (5.7pp), major in STEM (2.8pp), earn PhDs (2.1pp), and pursue research careers (4.7pp). These effects, which become increasingly long-term, outline a potentially causal story, especially given the sample and controls used in the estimation of these effects. An exceptional math student has a math mentor in high school who helps them acquire a credible signal of their ability (AMC 12 score) and increases their enthusiasm for STEM. This signal and an informed reference letter from the mentor helps the student get into a highly resourced technical school like MIT. At MIT the student is encouraged to continue pursuing STEM and have more exposure to researchers. This exposure encourages them to earn a PhD and/or pursue a research career.

[12] In future iterations, I will be using the SABS data on middle school and high school catchment areas to construct a similar measure of mentor exposure.

Despite my specialized sample, rich set of controls, and causal story, the estimates generated using OLS may be biased, which jeopardizes the causal interpretation of the OLS estimates. For example, differential mentor take up may reflect difference in student enthusiasm for mathematics that exist despite their common middle school math competition engagement. In this case, OLS would overestimate the impact of the math mentor because the estimated coefficient is also capturing the effect of STEM enthusiasm on later outcomes.

To address endogeneity concerns like these, I leverage variation in exposure to a high school Math League mentor for an instrumental variables strategy. More specifically, I use an indicator for whether the middle school a student attended was within five miles of a high school in the same district that offered Math League during the years the student was in high school ($exposure_{st}$) as an instrument for whether the student had a high school Math League mentor ($mentor_i$). If identification holds, the estimates generated using this IV strategy will be based on the local average treatment effect; they capture the causal effect of math mentors on the outcomes of the exceptional math students who are induced to have high school Math League mentors by their availability. These are the *compliers*. Similar to the previous analysis, I implement this IV with district and school fixed effects separately. I focus on the specification with district effects, but estimates with school fixed effects are similar, though noisier.

For this IV strategy, the exclusion restriction requires that the instrument—whether the student's middle school was near a high school with an active Math League mentor—affects the student's outcomes only through the likelihood of having a high school Math League mentor. In other words, the exclusion restriction assumes that being near a high school with a Math League mentor does not have a direct impact on the student's later academic or career outcomes beyond its effect on whether the student has a math mentor.

This assumption is strengthened by the fact that my analysis includes district fixed effects, meaning any differences in outcomes are not driven by broader district-level factors such as variation in funding or policies. By controlling for district fixed effects, I effectively limit the comparison to students who were subject to the same district-wide conditions but attended different high schools within the district. Moreover, the sample itself is quite homogenous: all students attended public, non-charter, non-magnet middle schools, participated in middle school math competitions, and demonstrated exceptional math ability based on their AMC performance. Given these similarities, the primary difference between students with and without a Math League mentor is their exposure to a high school with an active Math League program, further supporting the plausibility of the exclusion restriction. Therefore, the variation I leverage in exposure to a high school Math League mentor is likely to only affect the outcomes through its impact on the probability of having a mentor.

$$mentor_i = \alpha + \beta exposure_{st} + \gamma rank_i^{(MS)} + \tau_t + \sigma_s + X_{ist}\lambda + \varepsilon_{ist}. \quad (8)$$

$$y_i = \alpha + \beta \widehat{mentor}_{ist} + \gamma rank_i^{(MS)} + \tau_t + \sigma_s + X_{ist}\lambda + \varepsilon_{ist}. \tag{9}$$

I estimate the IV coefficients using two-stage least squares regression. For the first stage I regress $mentor_i$ on *exposure* while including all the controls from before. I then estimate the original equation, but use the predicted values $\widehat{mentor}$ as shown in Equation 9.

The F-stat for the first stage indicates the instrument is strong (Table 15). Students near a high school with an active Math League mentor ($exposure = 1$) are 9.6pp more likely to have a high school Math League mentor ($mentor = 1$) than those who are not ($exposure = 0$). The results suggest students who perform better on the AMC are more likely to have a high school Math League mentor (i.e. participate and earn a perfect score) even after controlling for exposure, which aligns with expectations.

The IV estimates are significant and larger than the OLS estimates (Table 16). This suggests that the students who are induced to have a math mentor by proximity to a high school with a Math League mentor–the compliers–experience larger effects from mentorship than the average student. These compliers may be especially responsive to these math mentors and the environments they cultivate because these students may lack adequate substitutes for the resources available to other students. These other students may be more advantaged: "always-takers" whose parents help them access a Math League school even if there is not one nearby, or "never-takers" who chose not to take-up because they have access to other opportunities or mentors. Unlike these non-compliers, who might have access to educational support regardless of Math League mentor availability, compliers may rely more heavily on these mentors as the only educators invested in their long-term outcomes. These mentors may be uniquely positioned to influence key decisions, such as college and major choice, due to the strength of their relationship with the students and their guidance throughout critical moments of academic development.

6 Estimating Missing Talent

In this section, I apply the zero-inflated negative binomial (ZINB) model from the previous section to estimate how many exceptional math students failed to be identified at the never Math League schools because their schools lacked a Math League mentor. I then apply the IV estimated mentor effects to determine how many more of these students would have attended a selective university, majored in STEM, earned PhDs, and pursued research careers in a back-of-the-envelope calculation.

6.1 Model Validation for Never Math League Schools

The analysis focuses on 8,193 non-magnet, public high schools in the NCES Common Core of Data (CCD) from 1994 to 2020 that *never* had a Math League mentor during that period; this is the never Math League sample from the previous section. I use the estimated ZINB model estimated using the high school entry Math League sample to estimate the amount of exceptional math talent revealed at these schools by the AMC, $talent_{st}^{(r)}$. For all the school-year observations in this sample $mentor_{st} = 0$, meaning $\hat{\beta}$ is never active. Consequently, the ZINB relies only on year fixed effects, community characteristics, and time-varying school characteristics to predict school participation in the AMC, $(1 - p_{st}^{inf})$, and exceptional math talent, $talent_{st}$.

The summary statistics for the *never* Math League sample used in this analysis and *entry* Math League sample– which first joined Math League between 1994 and 2020–are provided in Table 8b. As stated before, the samples differ in some important ways: the schools used to estimate the model tend to be located in more affluent and education areas and have higher proportions of White and Asian students. These demographic and socioeconomic differences may be associated with unobservable differences between these samples that could influence the model's predictive accuracy when applied to schools that have never participated in Math League, raising questions about generalizability. There may also be school types in the never Math League sample that are outside the support of the estimated ZINB model.

That said, the model performs well when viewed in aggregation. When aggregated by predicted top AMC counts, these predicted counts closely align with the realized top AMC counts for the schools during the period (Figure 7). This suggests the estimated model is performing well for schools of various types, though the model does appear to overestimate counts for the top schools.

The model also performs well when aggregating up to the state level. For this state level aggregation, I collapse all the school-year observations from 1994 to 2020 to the state level. I sum all the realized and predicted AMC counts and take the log to produce log counts for each state. The associated scatter plot reveals most states are close to the 45-degree line with the realized counts equal to predicted counts.

The realized counts fall quite short for some states like Hawaii, Idaho, Oklahoma, and Wyoming (Figure 8). Hawaii is a special case among these outliers; the model predicts the 34 schools in Hawaii would have produced roughly as many top AMC scorers as the 734 California schools in this sample during the period. For demographic reasons, these schools are outside the support of the estimated model, so I drop these 34 schools from the remainder of the analysis.[13] One possible explanation for the other outlier states is that for, idiosyncratic reasons, the schools in these states were relatively less likely to participate in the AMC during this period.[14] With the Hawaiian schools dropped, the average overestimate is a modest 7.2%.

[13]Hawaii is the only US state that is majority Asian, and the share of Asian students at Hawaiian high schools reflects this. The ZINB model, which is estimated on schools with comparatively low shares of Asian students (Table 11), finds the share of Asian students is a key predictor for both the inflate and count estimates. Together, these two facts produce the overestimates.

[14]For a long time, the AMC had state coordinators–often mathematics professors–who played a key role in encouraging school participation. It is possible the coordinators for these states were less successful at encouraging school participation.

6.2 Back-of-the-Envelope: Mentor Impact on Revealing and Influencing Talent

I now consider how expanding access to these math mentors might have changed the amount of exceptional talent revealed at these schools and their later outcomes. For this exercise, I again predict the number of top AMC scorers these schools produce, but now assert that $mentor_{st} = 1$ for all schools and time periods. Under this scenario, these 8,160 schools[15] would have produced 20,360 top AMC scorers, a 122% increase over the 9,092 top AMC scorers realized at these schools. These 11,168 additional students represent the *missing* exceptional math talents who would have participated in the AMC and been identified as exceptional if they had access to a mentor. In many states, especially in the Rocky Mountain region and the central South, the number of missing students is five times that of identified students (9).

I now consider how these mentors might have impacted the trajectories of these 11,168 missing students. I note these missing students align with the compliers from Section 5.2; these exceptional math students were induced into participating in the AMC by these mentors. I apply the IV estimated mentor effects to these students (Table 16a). Based on this exercise, these mentors would have increased the number of these students attending selective universities (3,017 students), majoring in STEM (3,465 students), earning PhDs (1,652 students), and pursuing careers as scientists and professors (1,850 students) during this twenty-seven year period.

This back-of-the-envelope calculation assumes these 8,160 schools could activate or hire teachers who could serve this role as well as the Math League mentors used to estimate the mentor effects. This seems highly unlikely. Nevertheless, the estimates here could be scaled easily to determine the impact of supplying teachers to a random subset of schools here. On average, how many of these schools would I need to supply with a mentor in order to discover a missing student next year? 20 schools. How many years would it take before these mentor effects *nudged* a missing student at one of these 20 schools into earning a PhD? 4.5 years.

Alternatively, I could instead use my model to identify a much smaller subset of schools where there appears to be a lot of missing talent (high predicted AMC counts, low realized AMC counts). Supplying these schools with mentors would be a much more efficient way to identify missing students and influence their later-in-life outcomes. Furthermore, it seems reasonable to believe such schools would be more likely to already have a teacher who could simply be encouraged or incentivized to fulfill this role.

7 Discussion

The findings in this paper have significant implications for both education policy and the broader economy. The results provide robust evidence supporting the "proficient mentor" hypothesis in

[15]Recall I dropped 33 schools from Hawaii.

the context of mathematics, suggesting that capable but not necessarily expert mentors can play a pivotal role in identifying and nurturing exceptional math talent. Importantly, my analysis shows that by simply activating or providing access to proficient mentors, we could reveal substantially more exceptional students and potentially change their educational and occupational trajectories.

It is important to emphasize that my analysis focuses specifically on the impact of these mentors on exceptional math students—those in the top 1% of mathematical ability. However, it is reasonable to believe that proficient mentors could have similar effects on highly capable and enthusiastic students who may not be at the extreme end of the ability spectrum. If the benefits of these mentors extend to students at, say, the 95th percentile in math ability, the aggregate impact of expanding access to such mentorship could be even greater than the effects identified in this paper.

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Tables

	AMC Sample		Ref. Sample	
	mean	sd	mean	sd
HS Cohort	2008.21	7.69	2008.21	7.69
Male	0.68	0.47	0.68	0.47
White	0.75	0.43	0.72	0.45
API	0.15	0.36	0.09	0.28
Other Race	0.09	0.29	0.20	0.40
Grad Share	0.27	0.12	.	.
MS AMC Rank	3,117.80	2,294.71	.	.
Top HS AMC	0.17	0.37	.	.
Math	0.09	0.29	0.02	0.12
STEM Major	0.48	0.50	0.21	0.41
Selective BA/BS	0.22	0.41	0.02	0.14
Earned PhD	0.08	0.27	0.02	0.13
Scientist/Professor	0.08	0.28	0.02	0.14
Observations	14,249		14,249	

(a) Middle School

	AMC Sample		Ref. Sample	
	mean	sd	mean	sd
HS Cohort	2003.93	8.75	2003.93	8.75
Male	0.75	0.43	0.75	0.43
White	0.68	0.47	0.74	0.44
API	0.25	0.43	0.08	0.27
Other Race	0.07	0.26	0.18	0.38
Grad Share	0.27	0.12	.	.
HS AMC Rank	2,382.07	1,644.69	.	.
Math Major	0.14	0.34	0.02	0.13
STEM Major	0.54	0.50	0.21	0.40
Selective BA/BS	0.31	0.46	0.02	0.15
Earned PhD	0.12	0.33	0.02	0.15
Research Career	0.11	0.31	0.02	0.14
Observations	24,434		24,434	

(b) High School

Table 1: This table provides summary statistics for the Linkedin matched AMC student samples. To construct the reference sample, I matched every AMC student in the AMC/LinkedIn match sample to another college graduate of the same gender who graduated in the same year.

	AMC Share	PhD Rate	Avg. MS AMC Rank
Math	0.09	0.18	2,691
Physics/Astronomy	0.03	0.36	2,721
Computer Science	0.12	0.07	2,999
Social Sciences	0.16	0.07	3,082
Chemistry/Biochemistry	0.03	0.22	3,093
Engineering	0.19	0.11	3,196
Bus/Fin/Acct/Marketing	0.14	0.01	3,214
Life Sciences	0.08	0.13	3,326
Geosciences	0.01	0.08	3,468
Observations	14,249		

(a) Middle School

	AMC Share	PhD Rate	Avg. HS AMC Rank
Computer Science	0.14	0.10	1,792
Math	0.14	0.23	1,852
Physics/Astronomy	0.05	0.43	2,148
Engineering	0.21	0.16	2,403
Chemistry/Biochemistry	0.04	0.31	2,498
Life Sciences	0.07	0.18	2,567
Social Sciences	0.14	0.08	2,577
Bus/Fin/Acct/Marketing	0.11	0.01	2,602
Geosciences	0.01	0.14	2,751
Observations	24,434	24,434	24,434

(b) High School

Table 2: The first column of this displays the share of the students in the LinkedIn matched AMC student samples who major in a given subject (double majors counted twice). The second column provides the rate at which students within given major pursue a PhD. The final column lists the average AMC rank of students in the sample with a given major.

	Top HS AMC	Selective BA/BS	STEM Major	PhD	Scientist/Professor
MS AMC Rank	0.0610***	0.0232***	0.0153***	0.00737***	0.00540***
	(0.00222)	(0.00225)	(0.00255)	(0.00144)	(0.00163)
Female	-0.0392***	-0.0405***	-0.190***	-0.00886*	-0.00378
	(0.00659)	(0.00771)	(0.00904)	(0.00492)	(0.00490)
Asian	0.0602***	0.0455***	0.0349**	-0.0106	0.00331
	(0.0112)	(0.0122)	(0.0144)	(0.00652)	(0.00767)
Other Race	0.00367	0.0317**	-0.00925	-0.0135	0.00549
	(0.0113)	(0.0136)	(0.0147)	(0.00836)	(0.00935)
HS Cohort FE	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes
Mean	0.168	0.221	0.481	0.0794	0.0848
N	14,249	14,249	14,249	14,249	14,249
Adj. R2	0.127	0.0617	0.0755	0.0311	0.00378

(a) Middle School

	Selective BA/BS	STEM Major	PhD	Scientist/Professor
HS AMC Rank	0.0134***	0.0164***	0.0125***	0.00438**
	(0.00220)	(0.00240)	(0.00186)	(0.00176)
Female	-0.0572***	-0.198***	-0.0214***	-0.00796*
	(0.00753)	(0.00813)	(0.00508)	(0.00453)
Asian	0.0456***	-0.00189	-0.0315***	0.0130**
	(0.0102)	(0.00845)	(0.00566)	(0.00553)
Other Race	0.0435***	-0.0188	-0.0160*	-0.00402
	(0.0122)	(0.0133)	(0.00900)	(0.00858)
HS Cohort FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
Mean	0.314	0.542	0.124	0.106
N	24,434	24,434	24,434	24,434
Adj. R2	0.0785	0.0823	0.0214	0.00873

(b) High School

Table 3: This table provides OLS estimates for a selection of coefficients from Equation 2. These coefficients are estimated using the Linkedin matched AMC student samples. The positive coefficients on AMC rank demonstrate these students sort by their math ability, while the other coefficients on speak to gaps in later-in-life outcomes. Standard errors are clustered at the school level.

Job Title Word	AMC Sample	Ref. Sample
md	45	0
cofounder	65	1
cs	84	6
phd	164	13
researcher	86	11
fellow	78	11
sr	90	13
professor	149	32
candidate	180	40
resident	112	25
scientist	184	47
software	721	192
physician	102	27
computer	114	32
strategy	94	27
science	199	60
mba	60	18
analytics	80	25
medicine	70	23
data	254	86
writer	54	19
engineer	1324	478
founder	69	25
research	225	84
product	192	72

(a) MS AMC

Job Title Word	AMC Sample	Ref. Sample
mit	38	0
quantitative	68	2
cofounder	83	2
cs	112	3
physics	45	3
phd	167	14
surgeon	38	3
trader	61	6
math	70	7
fellow	97	12
mathematics	62	8
scientist	252	34
researcher	105	17
resident	95	16
software	862	161
machine	52	10
professor	281	55
sr	117	25
physician	117	25
learning	73	18
data	303	77
candidate	116	32
computer	112	30
research	239	70
portfolio	39	12

(b) HS AMC

Table 4: These tables provide insight on the careers pursued by students in both LinkedIn matched AMC samples. The second column in these tables provides the number of AMC students out of 10,000 students who have the word in their primary job title on their LinkedIn profile. The third column shows the same frequency for the associated reference sample. The words are sorted by the ratio between the AMC sample and reference sample frequencies. The listed words are those that show up in the job titles of at least 0.5% of the AMC sample and have the highest frequency ratios.

Job Location	AMC Sample	Ref. Sample
capital one	17.5	0
lockheed martin	15.4	0
epic	15.4	0
university washington	14.7	0
mckinsey company	11.2	0
google	74.4	1.4
amazon	32.3	.7
microsoft	28.1	.7
apple	21.8	.7
meta	16.8	.7
university california berkeley	15.4	.7
facebook	13.3	.7
university pennsylvania	11.9	.7
uc berkeley	11.9	.7
purdue university	11.2	.7
mit	11.2	.7
harvard university	10.5	.7
university chicago	19.7	1.4
northwestern university	9.8	.7
duke university	9.8	.7
yale university	9.8	.7
stanford university	26	2.1
georgia institute technology	16.8	1.4
university texas at austin	14	1.4
university michigan	13.3	1.4

(a) MS AMC

Job Location	AMC Sample	Ref. Sample
facebook	28.6	0
mit	17.2	0
epic	14.7	0
princeton university	13.9	0
goldman sachs	11.9	0
jane street	10.6	0
mckinsey company	10.2	0
kaiser permanente	9.8	0
university illinois at urbanachampaign	9.4	0
harvard medical school	9	0
google	130.1	1.2
amazon	38.9	.4
apple	25	.4
microsoft	38.5	.8
intel corporation	14.3	.4
university washington	13.9	.4
yale university	13.1	.4
university california berkeley	13.1	.4
stanford university	25.8	.8
university pennsylvania	12.3	.4
cornell university	12.3	.4
northwestern university	11.9	.4
meta	22.1	.8
boeing	9	.4
nvidia	9	.4

(b) HS AMC

Table 5: These tables provide insight on the companies that employ students in both LinkedIn matched AMC samples. The second column in these tables provides the number of AMC students out of 10,000 students who list this company as their primary company on their LinkedIn profile. The third column shows the same frequency for the associated reference sample. The companies are sorted by the ratio between the AMC sample and reference sample frequencies. The listed companies are those that show up in the profiles of at least 0.1% of the AMC sample and have the highest frequency ratios.

	mean	sd
Male	0.44	0.50
White	0.99	0.11
Masters	0.44	0.50
PhD	0.00	0.00
Teacher	0.91	0.29
Math Teacher	0.84	0.37
Physics Teacher	0.02	0.15
Comp. Sci. Teacher	0.04	0.18
Principal	0.00	0.06
G&T Coordinator	0.08	0.27
Department Chair	0.04	0.20
Club Advisor	0.14	0.35
Athletic Coach	0.09	0.28
Total Teaching Experience	12.06	9.34
District Teaching Experience	9.44	8.76
Recent Hire (Dist. Exp. ≤ 3)	0.32	0.47
School's First ML Mentor	0.19	0.39
ML Mentor Years	3.50	3.38
Observations	257	

Table 6: This tables provides summary statistics for 257 Wisconsin Math League mentors during their first year of organizing the activity. The variable ML Mentor Years is the number of years a mentor served as Math League mentor at the school.

	mean	sd
HS Cohort	1991.44	12.64
Male	0.44	0.50
White	0.90	0.30
Asian	0.02	0.15
Non-Asian/White	0.08	0.27
University not Listed	0.53	0.50
Selective University	0.04	0.19
Major Not Listed	0.55	0.50
Education Major	0.09	0.28
Math Major	0.30	0.46
STEM Major	0.36	0.48
Masters	0.41	0.49
Education Masters	0.22	0.42
STEM Masters	0.12	0.32
PhD	0.04	0.19
Education PhD	0.03	0.18
STEM PhD	0.01	0.11
Observations	1,972	

Table 7: This tables provides summary statistics for 1,972 Math League mentors with LinkedIn profiles.

	Never Sample		Entry Sample		Early Sample	
	mean	sd	mean	sd	mean	sd
White Share	0.70	0.31	0.71	0.29	0.75	0.25
Asian Share	0.03	0.07	0.04	0.10	0.04	0.08
Black Share	0.11	0.20	0.11	0.19	0.10	0.16
Hispanic Share	0.16	0.24	0.14	0.20	0.11	0.17
Free Lunch Share	0.39	0.26	0.32	0.25	0.26	0.22
Population (1000s)	108.68	368.81	85.99	293.20	74.53	240.42
Income per Capita (1000s)	18.07	6.23	21.38	9.38	23.18	10.06
BA/BS Grad Ratio	0.12	0.07	0.15	0.10	0.18	0.11
Math League Ever	0.00	0.00	1.00	0.00	1.00	0.00
Math League Active	0.00	0.00	0.13	0.33	0.36	0.48
AMC 8 Top 3200 Scorer	0.02	0.13	0.04	0.20	0.08	0.26
AMC 8 Top 3200 Scorers	0.05	0.54	0.17	1.39	0.31	1.98
Observations	207,711		34,830		40,230	

(a) Middle School

	Never Sample		Entry Sample		Early Sample	
	mean	sd	mean	sd	mean	sd
White Share	0.75	0.29	0.76	0.26	0.73	0.27
Asian Share	0.02	0.06	0.04	0.08	0.05	0.09
Black Share	0.10	0.19	0.09	0.17	0.10	0.17
Hispanic Share	0.13	0.22	0.11	0.17	0.12	0.18
Free Lunch Share	0.33	0.24	0.24	0.21	0.22	0.20
Population (1000s)	52.03	226.74	64.96	197.55	75.85	215.63
Income per Capita (1000s)	17.42	5.23	20.73	8.08	23.37	10.18
BA/BS Grad Ratio	0.11	0.07	0.15	0.10	0.18	0.11
Math League Ever	0.00	0.00	1.00	0.00	1.00	0.00
Math League Active	0.00	0.00	0.21	0.41	0.51	0.50
Math League Honoree	0.00	0.00	0.08	0.26	0.18	0.38
Math League Honorees	0.00	0.00	0.25	1.47	0.62	2.18
AMC 10 Top 3200 Scorer	0.01	0.11	0.06	0.24	0.10	0.31
AMC 10 Top 3200 Scorers	0.03	0.34	0.18	1.28	0.30	1.60
AMC 12 Top 3200 Scorer	0.02	0.15	0.09	0.29	0.17	0.38
AMC 12 Top 3200 Scorers	0.04	0.38	0.24	1.23	0.50	1.79
Observations	221211		33102		33075	

(b) High School

Table 8: These table contains summary statistics for samples of public, non-charter, non-magnet middle schools and high schools that are present in the NCES data every year from 1994 to 2020. The Never Sample are the schools that never participated in Math League during this period. The Entry Sample are the schools that started participating in Math League after 1994. The Early Sample are the schools that were already participating in Math League in 1994.

	(1)	(2)	(3)
Mentor	1.247***	0.971***	0.976***
	(0.0808)	(0.0796)	(0.0576)
City Pop. (log)	0.292***	0.235***	0.0679
	(0.0255)	(0.0269)	(0.0456)
City BA Share	11.84***	6.225***	-2.986***
	(0.617)	(0.617)	(0.996)
City Income (per capita)	-0.0381***	-0.0132***	0.0128*
	(0.00453)	(0.00452)	(0.00679)
Free Lunch Share	-1.135***	-0.0299	-1.663***
	(0.293)	(0.336)	(0.358)
School Enrollment (log)	1.061***	0.514***	0.756***
	(0.0729)	(0.0832)	(0.131)
Asian Student Share	3.640***	3.404***	2.518***
	(0.297)	(0.270)	(0.333)
Year FE	Yes	Yes	Yes
Schl FE	No	No	Yes
Technique	NB	NB	NB
Mean	0.173	0.716	0.716
N	34766	8414	8414
Log-Likelihood	-7647.8	-6468.0	-4956.7

Standard errors in parentheses

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

Table 9: This table presents coefficients from Equation 3 estimated using negative binomial regression and the middle school entry Math League sample. The coefficients of interest are those associated with Mentor, which capture the impact of middle school Math League mentors on the number of top AMC scorers at a school in log odds. The estimated coefficients provide evidence that Math League mentors increase the number of top AMC scorers at schools. Standard errors are clustered at the school level.

	(1)	(2)	(3)
Mentor	0.743***	0.592***	0.385***
	(0.0426)	(0.0412)	(0.0400)
City Pop. (log)	0.265***	0.185***	-0.0225
	(0.0156)	(0.0156)	(0.0472)
City BA Share	11.13***	7.385***	5.082***
	(0.383)	(0.376)	(1.111)
City Income (per capita)	-0.0511***	-0.0331***	-0.0365***
	(0.00412)	(0.00397)	(0.0105)
Free Lunch Share	-0.839***	-0.212	-0.0746
	(0.214)	(0.234)	(0.318)
School Enrollment (log)	1.333***	0.834***	0.948***
	(0.0507)	(0.0520)	(0.105)
Asian Student Share	3.065***	2.951***	4.508***
	(0.184)	(0.174)	(0.365)
Year FE	Yes	Yes	Yes
Schl FE	No	No	Yes
Technique	NB	NB	NB
Mean	0.245	0.660	0.660
N	33,041	12,238	12,238
Log-Likelihood	-11679.5	-10517.2	-8127.6

Standard errors in parentheses

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

Table 10: This table presents coefficients from Equation 3 estimated using negative binomial regression and the high school entry Math League sample. The coefficients of interest are those associated with Mentor, which capture the impact of high school Math League mentors on the number of top AMC scorers at a school in log odds. The estimated coefficients provide evidence that Math League mentors increase the number of top AMC scorers at schools. Standard errors are clustered at the school level.

	Middle School		High School	
	Inflate Model	Count Model	Inflate Model	Count Model
Mentor	-1.271***	0.166	-0.879***	0.419***
	(0.175)	(0.113)	(0.206)	(0.111)
City Pop. (log)	-0.102	0.237***	-0.0540	0.222***
	(0.0678)	(0.0515)	(0.0840)	(0.0514)
City BA Share	-2.916	8.054***	-8.418***	6.919***
	(1.815)	(1.574)	(2.756)	(1.290)
City Income (per capita)	0.0108	-0.0163	0.0496**	-0.0300***
	(0.0146)	(0.0112)	(0.0230)	(0.0108)
Free Lunch Share	4.653***	3.968***	-0.341	-0.724
	(0.682)	(0.760)	(1.650)	(1.002)
School Enrollment (log)	-0.571***	0.693***	-1.293***	0.615***
	(0.212)	(0.258)	(0.281)	(0.165)
Asian Student Share	-1.622***	3.380***	-17.98***	1.237**
	(0.534)	(0.557)	(6.966)	(0.599)
Year FE	Yes		Yes	
Schl FE	No		No	
Technique	ZINB		ZINB	
Mean	0.173		0.245	
N	34766		33041	
Log-Likelihood	-7295.4		-11395.9	

Standard errors in parentheses

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

Table 11: This table presents coefficients from Equation 3 estimated using zero-inflated, negative binomial regression and the both the middle school and high school entry Math League samples. The coefficients on Mentor in the Inflate portion of these models capture the impact of Math League mentors on schools non-participation in the AMC in log odds. The coefficients on Mentor in the Count portion of these models capture the impact of Math League mentors the number of top AMC scorers at an AMC participating school in log odds. The estimated coefficients provide evidence that Math League mentors increase the number of top AMC scorers at schools by increasing AMC participation and through other mechanisms. Standard errors are clustered at the school level.

	(1)	(2)	(3)
Mentor	0.464***	0.488***	0.808***
	(0.110)	(0.108)	(0.0792)
Free Lunch Share	-2.119***	-0.875**	-1.999***
	(0.318)	(0.366)	(0.381)
Mentor × Free Lunch Share	3.789***	2.748***	1.150***
	(0.399)	(0.448)	(0.363)
City Pop. (log)	0.293***	0.235***	0.0687
	(0.0257)	(0.0269)	(0.0457)
City BA Share	11.81***	6.236***	-2.911***
	(0.612)	(0.613)	(0.998)
City Income (per capita)	-0.0385***	-0.0141***	0.0125*
	(0.00450)	(0.00448)	(0.00679)
School Enrollment (log)	1.105***	0.560***	0.766***
	(0.0732)	(0.0830)	(0.131)
Asian Student Share	3.563***	3.315***	2.463***
	(0.294)	(0.269)	(0.334)
Year FE	Yes	Yes	Yes
Schl FE	No	No	Yes
Technique	NB	NB	NB
Mean	0.173	0.716	0.716
N	34766	8414	8414
Log-Likelihood	-7603.1	-6448.6	-4951.8

Standard errors in parentheses

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

Table 12: This table presents coefficients from Equation 6 estimated using negative binomial regression and the middle school entry Math League sample. The coefficients of interest are those associated with Mentor and Mentor X Free Lunch Share, which capture the impact of middle school Math League mentors on the number of top AMC scorers at a school in log odds and differential effects by schools' share of free lunch eligible students. The estimated coefficients provide evidence that Math League mentors increase the number of top AMC scorers at schools and have a larger, proportional, effect at disadvantaged schools. Standard errors are clustered at the school level.

	No Mentor		Mentor	
	mean	sd	mean	sd
HS Cohort	2009.95	5.87	2011.31	5.40
Male	0.67	0.47	0.69	0.46
White	0.76	0.43	0.67	0.47
Asian	0.15	0.36	0.23	0.42
Non-Asian/White	0.09	0.28	0.10	0.30
City Pop. (log)	10.78	1.57	10.93	1.53
City BA Share	0.28	0.11	0.31	0.12
City Income (per capita)	30275.47	12600.01	34572.98	14251.10
MS AMC Rank	1824.62	1304.02	1588.79	1268.13
Mentor Near MS	0.46	0.50	0.66	0.47
Top HS AMC	0.13	0.34	0.32	0.47
STEM Major	0.49	0.50	0.58	0.49
Selective BA/BS	0.19	0.39	0.29	0.45
Earned PhD	0.08	0.27	0.09	0.29
Scientist/Professor	0.09	0.29	0.11	0.32
Observations	7,192		1,527	

Table 13: This table provides summary statistics on students from the LinkedIn matched middle school AMC sample who attended public, non-charter, non-magnet middle schools and graduated high school between 1998 and 2020. Those in subsample (1) were not high school Math League scorers. Those in subsample (2) were high school Math League scorers. Given the ability demonstrated by these students in middle school, I consider being a high school Math League scorer a good proxy for participating in Math League.

	Top HS AMC	Selective BA/BS	STEM Major	Earned PhD	Research Career
Mentor	0.157***	0.0575***	0.0376**	0.0217**	0.0171*
	(0.0107)	(0.0124)	(0.0153)	(0.00849)	(0.00924)
MS AMC Rank	0.0482***	0.0218***	0.0141***	0.00678***	0.00600***
	(0.00192)	(0.00222)	(0.00274)	(0.00152)	(0.00166)
Mean	0.163	0.206	0.509	0.0794	0.0938
Location FE	District	District	District	District	District
N	8719	8719	8719	8719	8719
Adj. R-squared	0.160	0.0688	0.0741	0.0218	0.00322

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(a) OLS with District Fixed Effects

	Top HS AMC	Selective BA/BS	STEM Major	Earned PhD	Research Career
Mentor	0.157***	0.0563***	0.0290*	0.0210**	0.0131
	(0.0110)	(0.0127)	(0.0157)	(0.00868)	(0.00948)
MS AMC Rank	0.0482***	0.0213***	0.0146***	0.00588***	0.00552***
	(0.00199)	(0.00230)	(0.00283)	(0.00157)	(0.00171)
Mean	0.163	0.206	0.509	0.0794	0.0938
Location FE	School	School	School	School	School
N	8719	8719	8719	8719	8719
Adj. R-squared	0.162	0.0654	0.0727	0.0235	0.0000866

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) OLS with School Fixed Effects

Table 14: This table presents the estimated coefficient on Mentor from Equation 7 for various student level outcomes. Estimates are provided for specification with district fixed effects and school fixed effects separately, with those generated using school fixed effects being slightly smaller. The highly significant, positive coefficients provide evidence mentors influence students outcomes beyond high school. Standard errors are clustered at the school level.

	Mentor
Near HS Mentor	0.0912***
	(5.98)
MS AMC Rank	0.0144***
	(7.20)
Female	-0.0194*
	(-2.30)
Asian	0.0134
	(1.14)
Non-Asian/White	0.00768
	(0.54)
Mean	0.2123
N	8,719
F-Stat	35.78

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(a) First Stage with District Fixed Effects

	Mentor
Near HS Mentor	0.0779***
	(3.87)
MS AMC Rank	0.0151***
	(7.32)
Female	-0.0153
	(-1.77)
Asian	0.0140
	(1.16)
Non-Asian/White	0.00349
	(0.24)
Mean	0.2123
N	8,719
F-Stat	14.97

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(b) First Stage with School Fixed Effects

Table 15: These tables show the first stage (Equation 8) for the instrument Near HS Mentor, an indicator for a student's middle school being within five miles of a high school that offers Math League during the years the student would be in high school. The F-statistic indicates the instrument is strong for both specifications. The coefficients on the covariates suggest mentor take up is higher for students with better middle school AMC scores and for male students. Standard errors are clustered at the school level.

	Top HS AMC	Selective BA/BS	STEM Major	Earned PhD	Scientist/Professor
Mentor	0.340**	0.411**	0.472**	0.225*	0.252*
	(0.163)	(0.194)	(0.239)	(0.131)	(0.143)
MS AMC Rank	0.0456***	0.0167***	0.00780*	0.00383	0.00260
	(0.00307)	(0.00365)	(0.00450)	(0.00247)	(0.00270)
Mean	0.163	0.206	0.509	0.0794	0.0938
Location FE	District	District	District	District	District
N	8719	8719	8719	8719	8719
Adj. R-squared	0.0131	-0.169	-0.136	-0.142	-0.172

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(a) IV with District Fixed Effects

	Top HS AMC	Selective BA/BS	STEM Major	Earned PhD	Scientist/Professor
Mentor	0.314	0.526*	0.545	0.250	0.344
	(0.249)	(0.308)	(0.374)	(0.203)	(0.228)
MS AMC Rank	0.0458***	0.0142***	0.00677	0.00241	0.000516
	(0.00425)	(0.00527)	(0.00639)	(0.00347)	(0.00390)
Mean	0.163	0.206	0.509	0.0794	0.0938
Location FE	School	School	School	School	School
N	8719	8719	8719	8719	8719
Adj. R-squared	-0.0247	-0.311	-0.240	-0.220	-0.317

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) IV with School Fixed Effects

Table 16: The tables provide the IV estimated mentor effects (Equation 9) for various outcomes. The estimates are significant, positive and much larger than the OLS estimates, suggesting they were biased downwards. Standard errors are clustered at the school level.

Figures

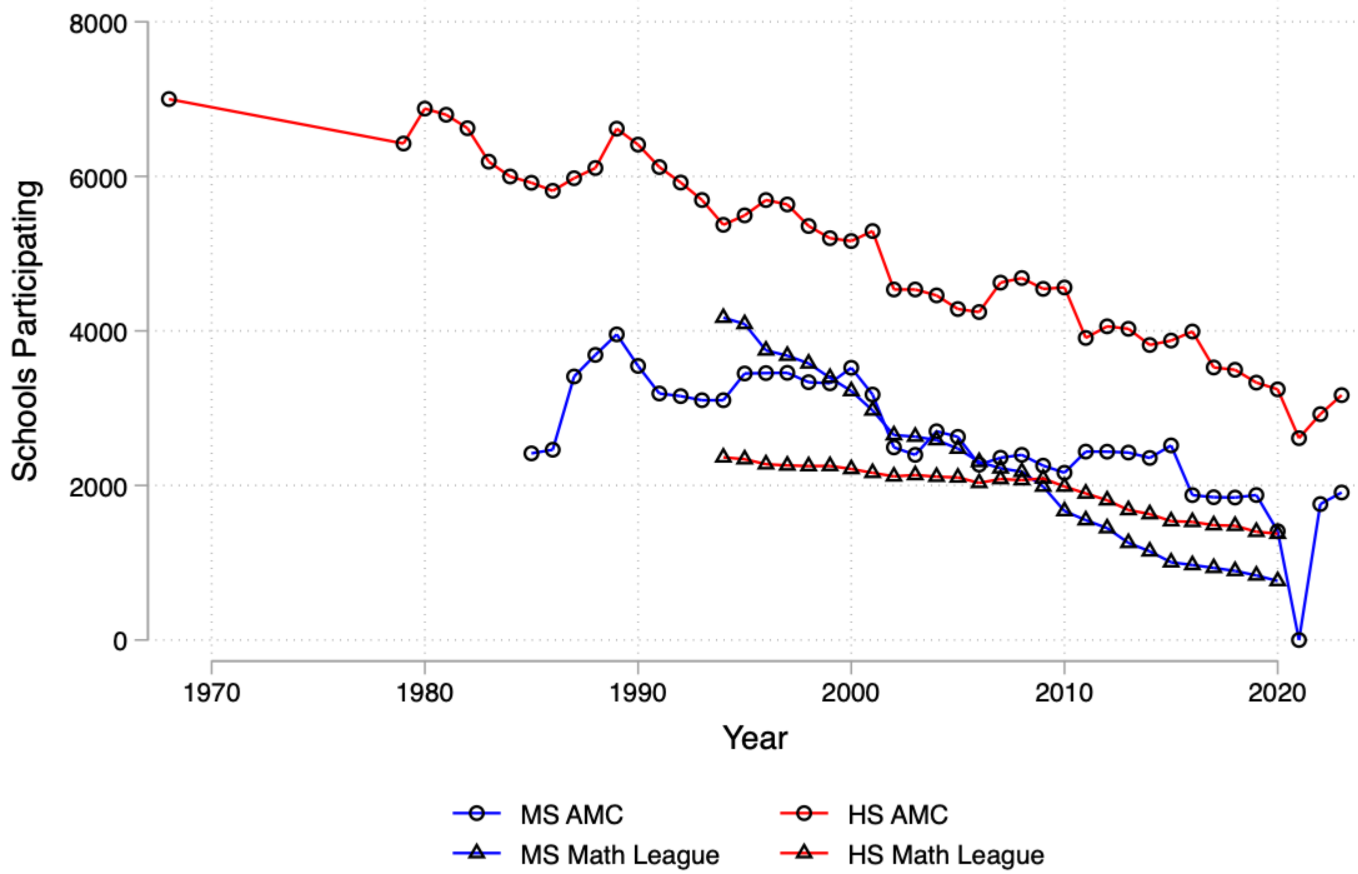


Figure 1: This figure shows the number of US middle schools and high schools participating in various math competitions across years. With fewer and fewer schools participating, there are likely more and more exceptionally talented math students being "missed" by these competitions.

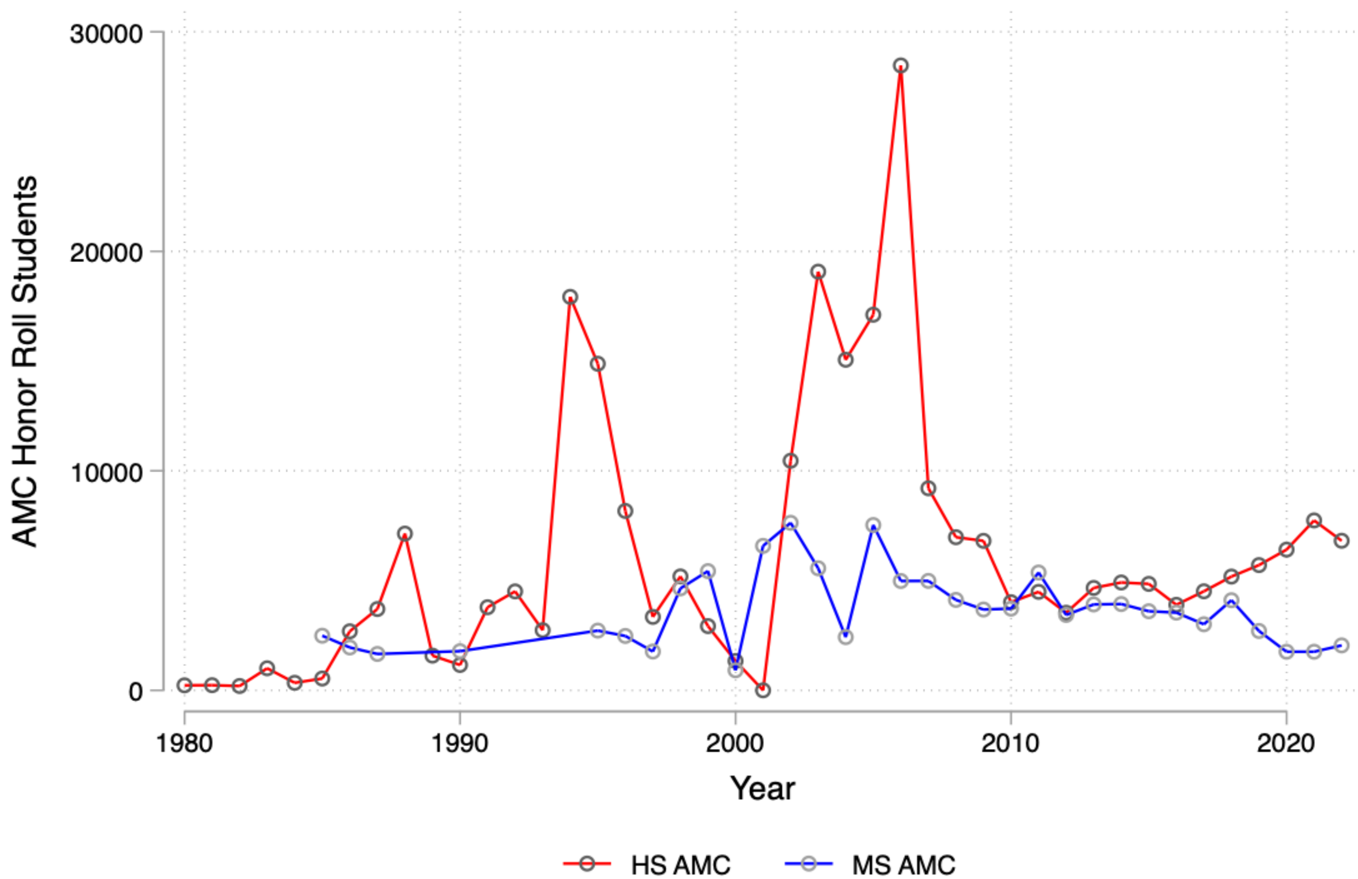
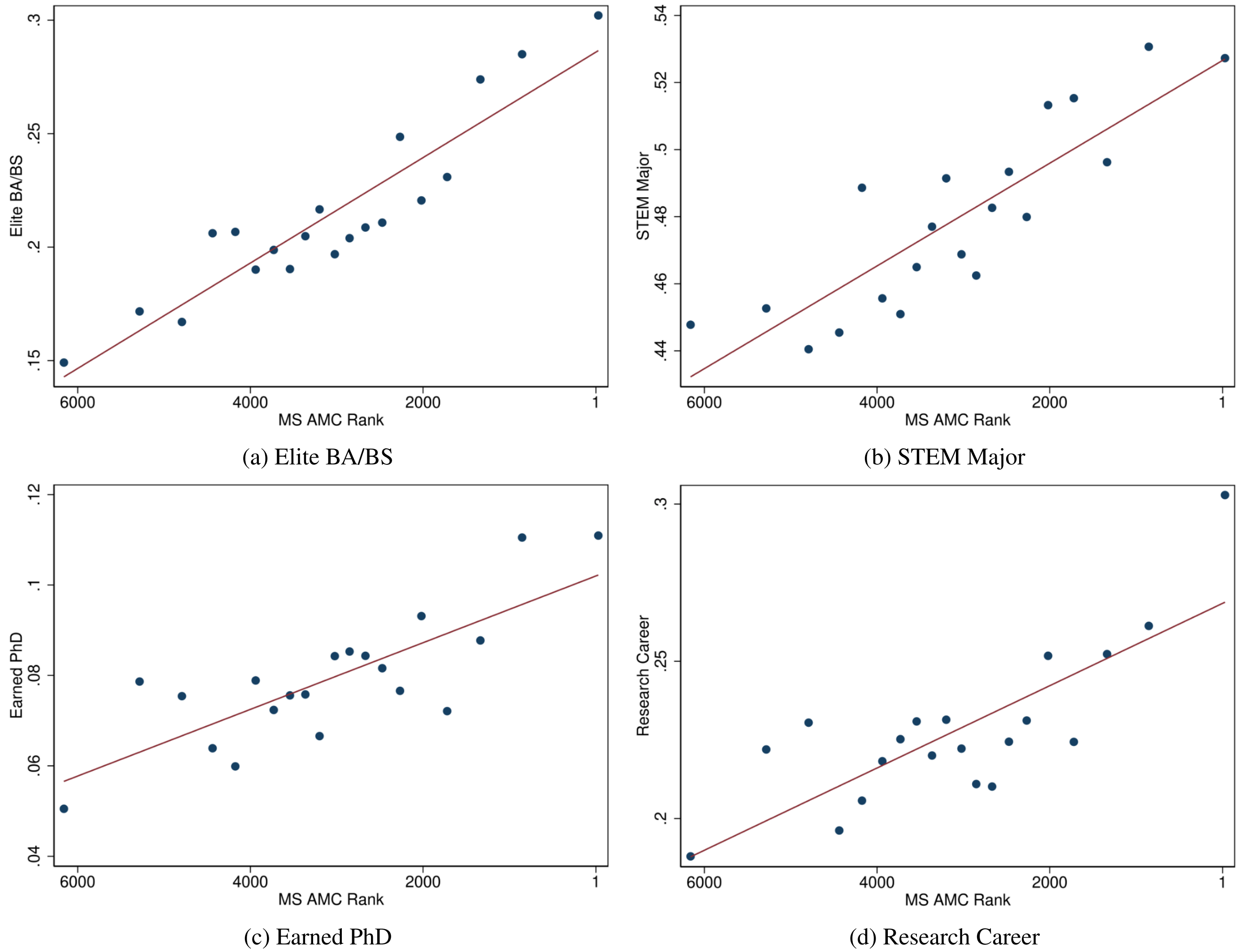


Figure 2: This figures displays the number of observable middle school (MS) and high school (HS) students honored by the AMC each year for their performances. The spikes are driven by shocks in the difficulty of the competitions and/or the AMC honor roll policies. The commentary from the AMC summaries suggest some of these shocks are intentional while others are not.



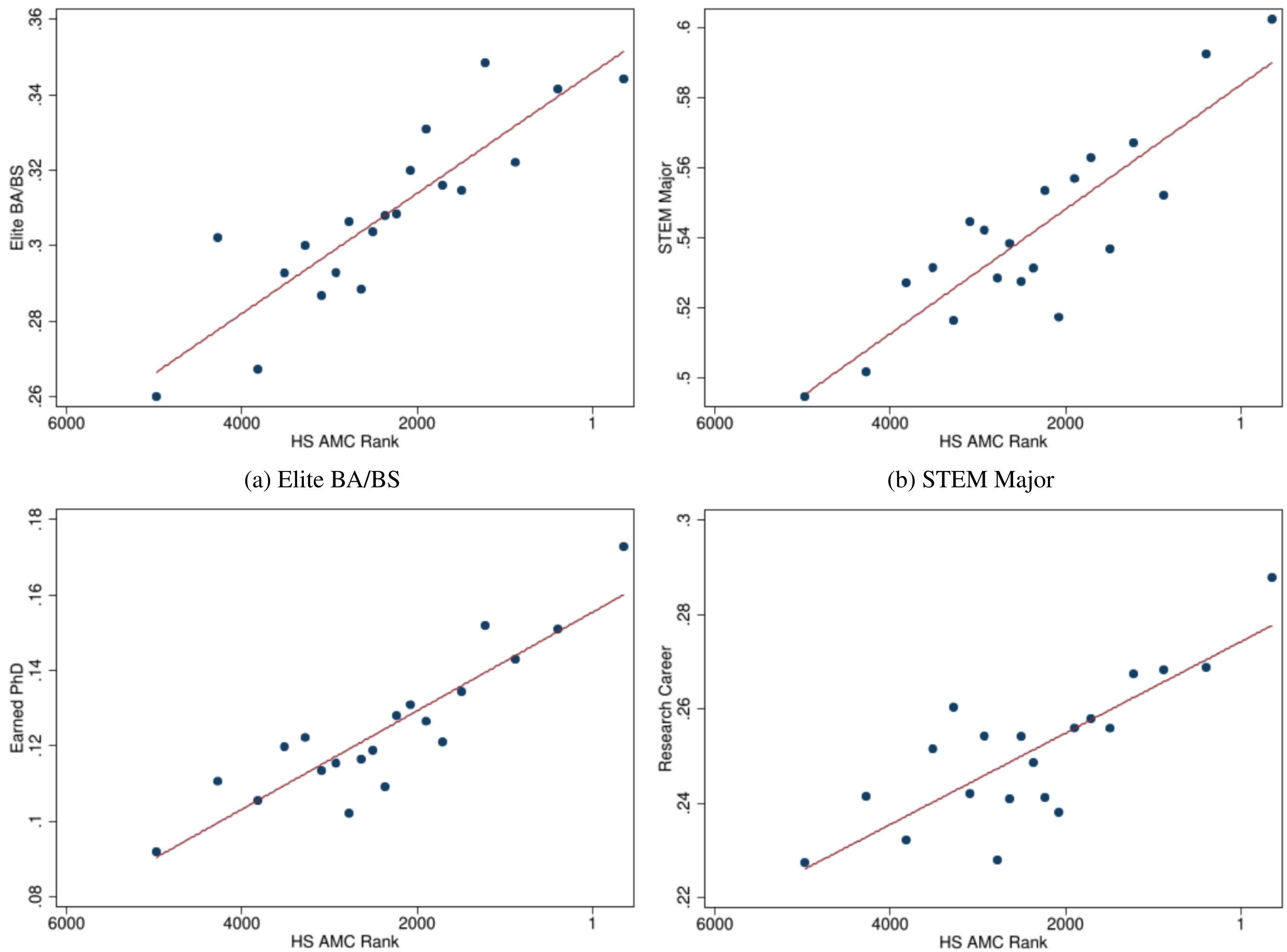
(a) Elite BA/BS

(b) STEM Major

(c) Earned PhD

(d) Research Career

Figure 3: This figure displays a series of binned scatter plots between AMC 8 rank and later-in-life outcomes for students in the matched AMC/LinkedIn sample. These plots are constructed while controlling for student gender, race, high school cohort, share of college graduates in high school city, test fixed effects (e.g. observation based on 2012 AMC 8), grade fixed effects (e.g. observation taken while student was in 7th grade), and state fixed effects



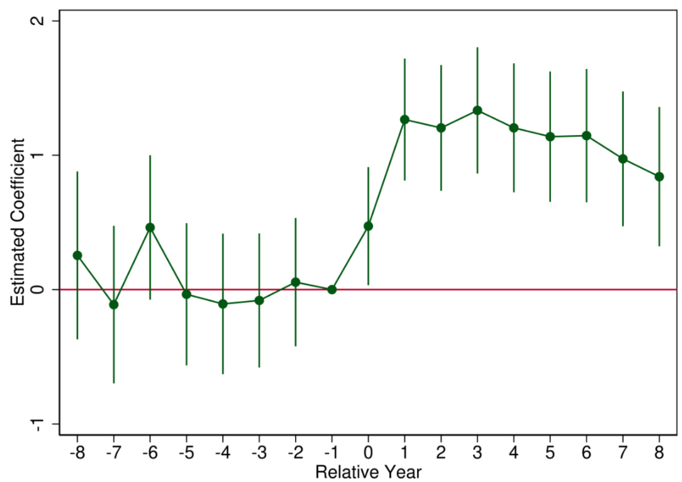
(a) Elite BA/BS

(b) STEM Major

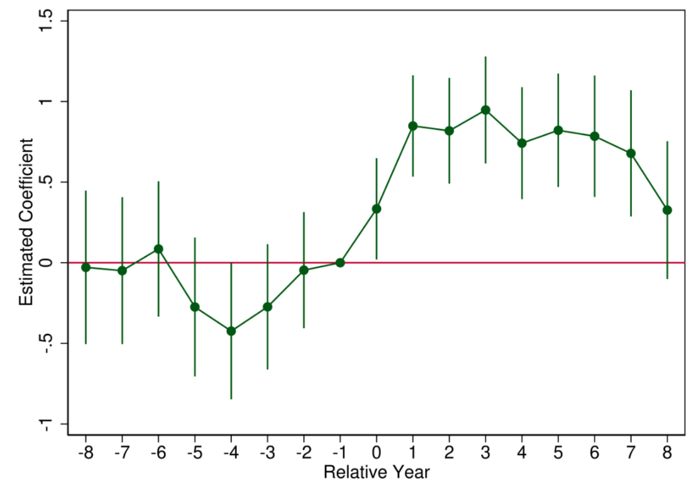
(c) Earned PhD

(d) Research Career

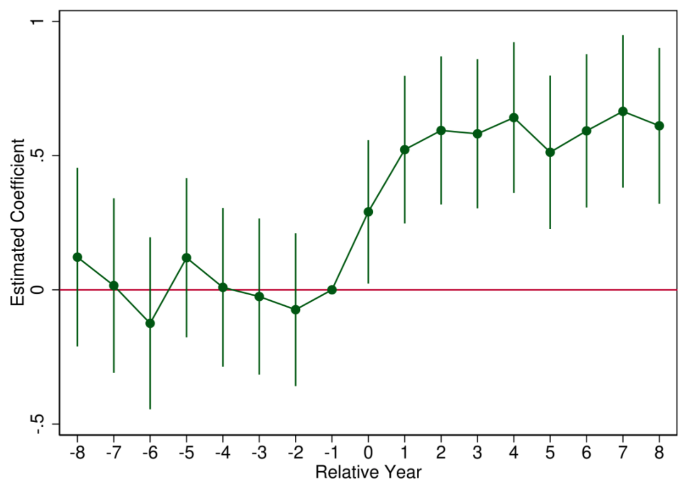
Figure 4: This figure displays a series of binned scatter plots between AMC 10/12 rank and later-in-life outcomes for students in the matched AMC/LinkedIn sample. These plots are constructed while controlling for student gender, race, high school cohort, share of college graduates in high school city, test fixed effects (e.g. observation based on 2012 AMC 10 A), grade fixed effects (e.g. observation taken while student was in 11th grade), and state fixed effects



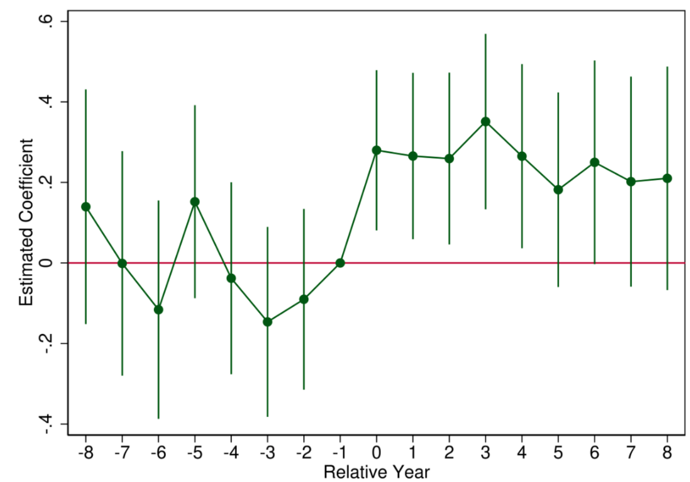
(a) Middle School, No School FE



(b) Middle School, School FE

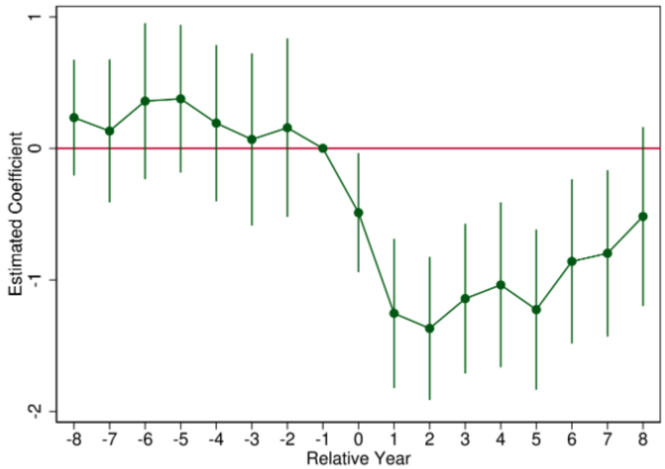


(c) High School, No School FE

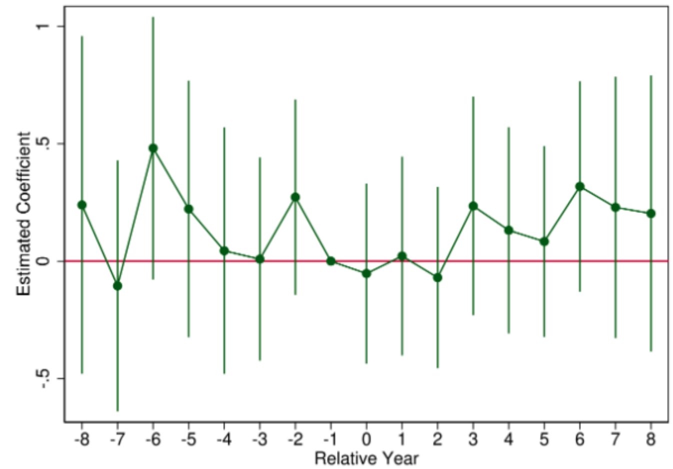


(d) High School, School FE

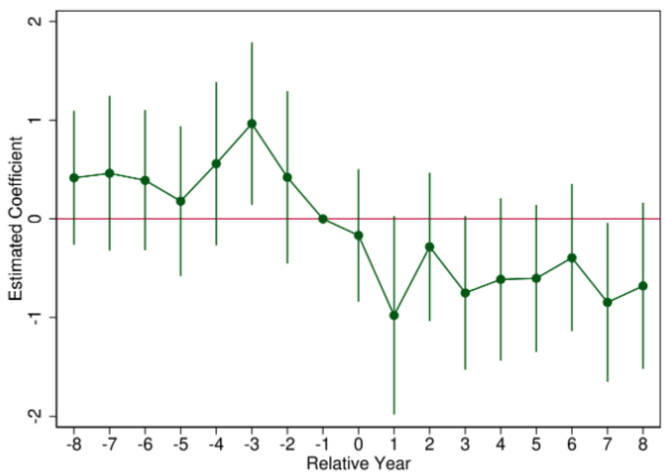
Figure 5: These figures display the negative binomial estimated event study coefficients from Equation 4 with 95% confidence intervals. The relative year coefficients are centered on the first year a school had a Math League mentor. Standard errors are clustered at the school level.



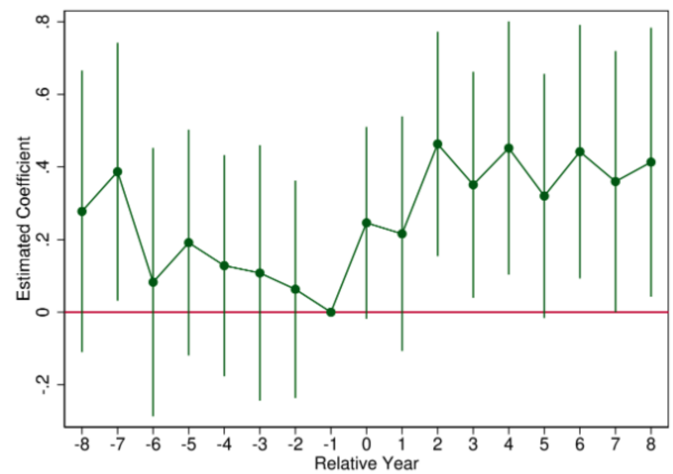
(a) Middle School (Inflate)



(b) Middle School (Count)



(c) High School (Inflate)



(d) High School (Count)

Figure 6: These figures display the zero-inflated, negative binomial estimated event study coefficients from Equation 4 with 95% confidence intervals. The relative year coefficients are centered on the first year a school had a Math League mentor. Standard errors are clustered at the school level.

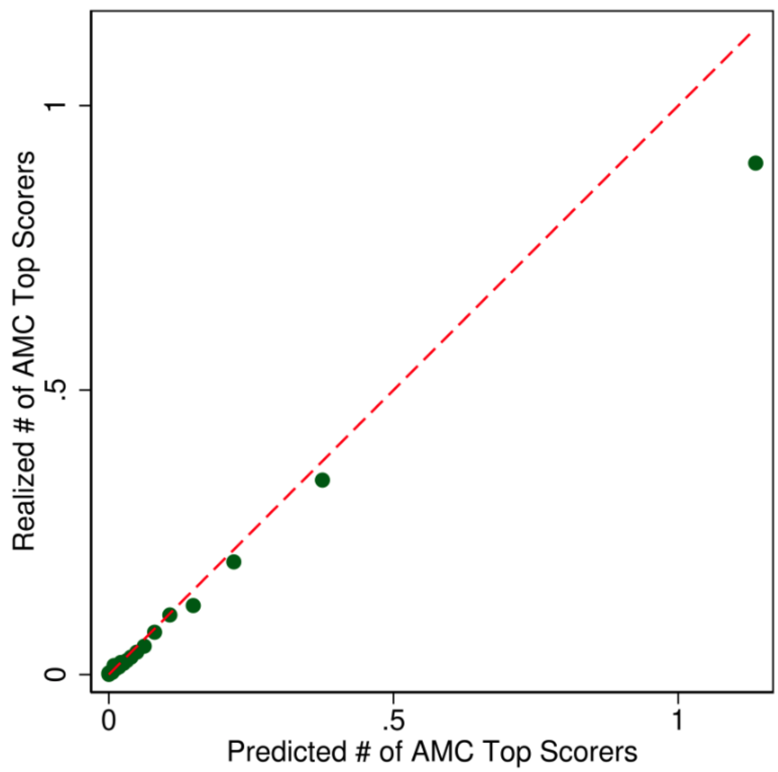


Figure 7: This binned scatter plot with twenty bins is constructed using the sample of public, non-magnet, non-charter high schools that never participated in Math League (Table 8b). It displays the relationship between the number of realized top AMC 12 scorers at a school in a given year and the number predicted using the high school zero-inflated negative binomial model estimated in Section 4.1 and documented in Table 10.

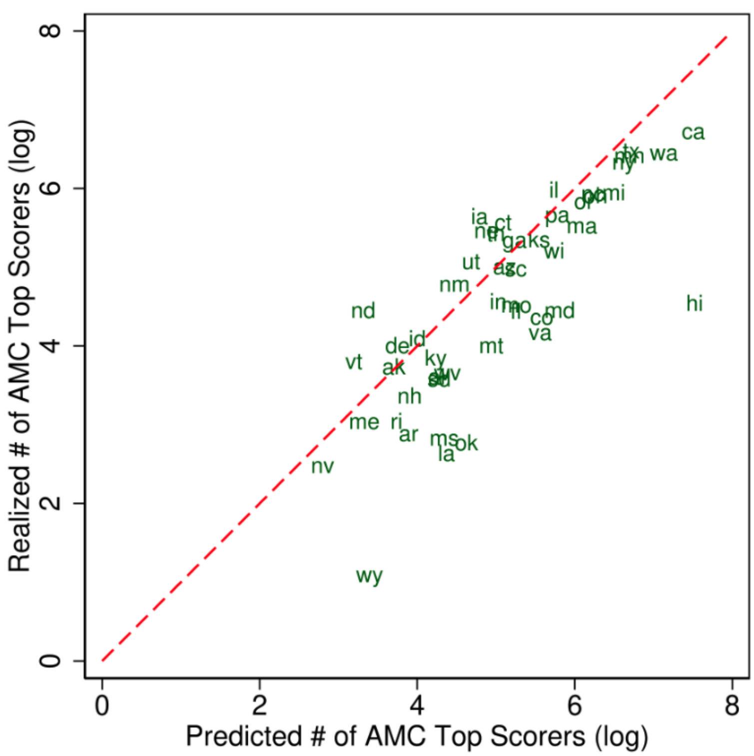


Figure 8: This binned scatter plot is constructed using the sample of non-magnet, non-charter public schools that never participated in Math League (Table 8b). It displays the relationship between the log total number of realized top AMC 12 scorers within a state from 1994 to 2020 and the log number predicted using the zero-inflated negative binomial model estimated in Section 4.1 and documented in Table 10.

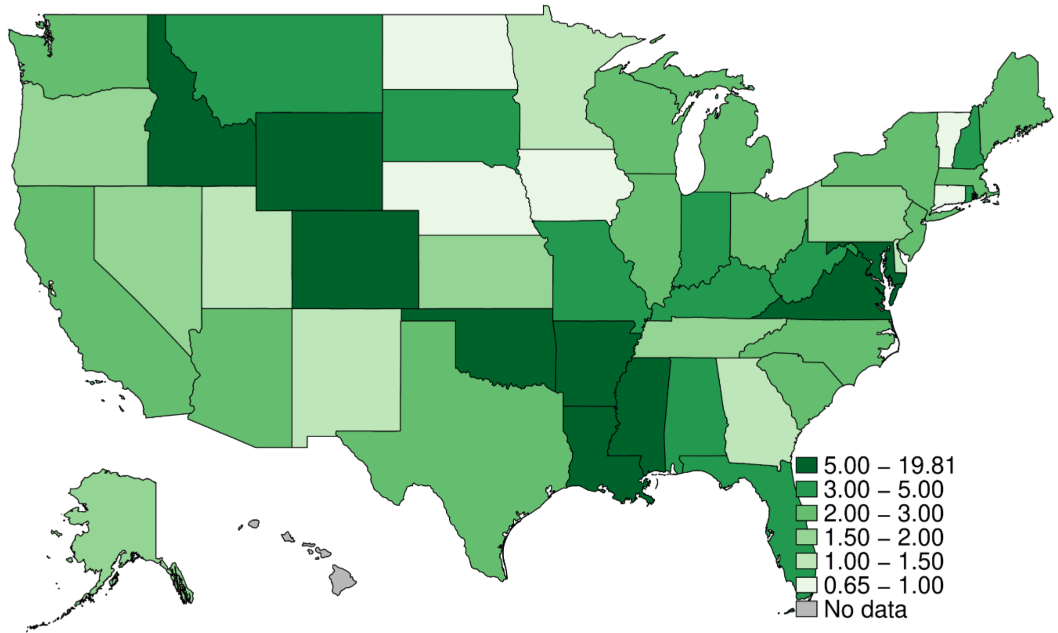


Figure 9: To construct this map, I predict the number of top AMC scorers produced by schools in the never Math League sample from 1994 to 2020 using the high school zero-inflated negative binomial model documented in Table 10 while asserting that every school had a Math League mentor. I then sum these predicted counts by state to obtain statewide prediction for this period. I also sum the realized top AMC scorer counts by states during this period. The states in this map are colored based on the ratio of the predicted top AMC counts to the realized counts, where states with a higher ratio are colored more darkly. This map suggests there are many "missing" exceptional math students who could have identified if only they had a mentor (Section 6.2).

A Framework For School-Based Mentors

In this appendix I provide a conceptual framework for understanding the impact of an activity-specific, school-based mentor on students and schools. Examples of such mentors include athletic coaches, theatre directors, and math competition coaches. These mentors provide students with the opportunity to engage in the activity and refine related skills. I define two measures of productivity for these mentors: a school value-added measure and a student value-added measure, which may differ substantially for a given mentor. I then discuss how this framework applies to math mentors and exceptional math students.

A.1 Mentor Value-Added

My model is closely related to teacher value-added models, but differs from traditional models in two important ways. First, while most teacher value-added models assume a student has a teacher, I allow for the possibility a student does not have a mentor for a given activity. Second, given a school has a mentor for an activity, students are not forced to participate, but rather select into participation themselves, are encouraged by their parents, or are recruited by a mentor.

Consider a student $i \in N$ at school s with mentor j in activity k. The student works towards a goal of some achievement or honor in the activity a_{ijk}. For example, this could mean qualifying for the All-State Orchestra as a violinist. The activity-specific, achievement, a_{ijk}, for this student is given by the sum of weighted student characteristics $\beta_k X_i$ and the student value-added of mentor j:

$$a_{ijk} = \beta_k X_i + \mu_{jk}^{stud} + \varepsilon_{ijk}. \tag{10}$$

This student achievement is realized if and only if the student participates in the activity and may vary by mentor. The indicator $\mathbb{I}_{ijk}$ captures whether student i participates in activity k given it is organized by mentor j. The achievement realized by student i is conditional on mentor j organizing the activity and is given by the product of a_{ijk} and this participation indicator

$$a_{ijk}^{*} = \left(\beta_k X_i + \mu_{jk}^{stud}\right) \mathbb{I}_{ijk} + \varepsilon_{ijk}. \tag{11}$$

Let $M_{jk} \subseteq N$ be the set of students who participate in activity k when it is organized by mentor j. I define the activity-specific, school achievement to be the sum of the achievements of those participating in the activity:

$$A_{sjk}^{*} = \sum_{i \in N} a_{ijk}^{*} = \sum_{i \in M_j} \left(\beta_k X_i + \mu_{jk}^{stud}\right) \mathbb{I}_{ijk} + \varepsilon_{sjk}. \tag{12}$$

Alternatively, I can write school achievement as the product of the number of the participating students and the average student achievement

$$A_{sjk}^{*} = |M_{jk}| \left(\beta_k \bar{X}_{jk} + \mu_{jk}^{stud}\right), \tag{13}$$

where $\bar{X}_{jk}$ are the average student characteristics of students in M_{jk}. That is, $\bar{X}_{jk} = \frac{1}{|M_{jk}|} \sum_{i \in M_{jk}} X_i$. This equation highlights the three mechanisms through which a mentor can influence school achievement in the activity. I refer to these as recruitment, selection, and improvement. Recruitment is the number of students who participate $\left|M_{jk}\right|$. Mentors can vary in their ability and/or desire to grow an activity. Selection refers to the average student characteristics of the recruited students and is denoted by $\bar{X}_{jk}$. The final mechanism, improvement, is the student value-added μ_{jk}^{stud} which captures the mentor's ability to improve student ability in the activity.

Let $j = 0$ correspond to the absence of a mentor. In the case of no mentor, $a_{i0k}^{*} = 0$ and, consequently, $A_{s0k}^{*} = 0$. Because of this, students and schools may benefit from a mentor, even a relatively low-quality mentor, because he provides access to the activity. As an example, consider a math coach whose only contribution is facilitating the AMC and Math League. Students at the school interested in the activity regardless of the mentor are able to participate in the competitions, gather accolades and signals of their ability, and connect with similarly interested peers despite the uninterested mentor. While teacher value-added models typically consider relative quality because a student always has a teacher, no mentor at all is a valid counterfactual in this case.

Nevertheless, A_{sj}^{*} is a poor measure of a mentor's productivity at the school-level. Schools may vary substantially by student ability within an activity due to school or community characteristics. Naturally, schools in Santa Cruz, California would have more success with a surfing club, while schools in Boulder, Colorado would have more success with a ski club. To build a better measure of school-level mentor productivity, I separate these influential characteristics from the mentor effects, giving me the following decomposition:

$$A_{sjk}^{*} = \gamma_k Z_s + \mu_{jk}^{schl}, \tag{14}$$

where Z_{st} are school characteristics and μ_{j}^{schl} is the school-level mentor effect. This serves as the school analog to Equation 11, and I refer to μ_{jk}^{schl} as mentor j's school value-added in activity k. Considering counterfactuals over mentor quality is easier here; a mentor with with higher μ_{j}^{schl} leads to greater school achievement regardless of the school. By combining equations 13 and 14, the relationship between school value-added and and school value-added can be written as:

$$\mu_{jk}^{schl} = \left|M_{jk}\right| \left(\beta \bar{X}_{jk} + \mu_{jk}^{stud}\right) - \gamma_k Z_s. \tag{15}$$

The difference between μ_{jk}^{stud} and μ_{jk}^{schl} here is subtle. While μ_{jk}^{stud} depends only on the mentor's ability to impact student achievement, μ_{jk}^{schl} depends on this ability as well as the mentor's ability to recruit students (M_{jk}) and the type of students they recruit $\bar{X}_{jk}$. As an example, consider a music teacher who recruits students for her school's orchestra program. Her student value-added represents her ability to increase a students' ability to play an instrument. Her school value-added depends on this student-value added as well as the number of students she can recruit and the quality of those students.

A.2 Framework Applied to Math Mentors

In this paper, I apply this framework to math competition coaches, whom I refer to as math mentors. I am interested in a couple specific impacts these math mentors may have on schools and students. First, I am interested in the impact these mentors have on the amount of revealed talent at their schools. In this case, a_{ijk}^{*} is an indicator for a student doing particularly well on a math competition and A_{ijk}^{*} is the number of such students at the school. A math mentor helps reveal talent if A_{ijk}^{*} increases in their presence, which is also captured by the school value-added measure μ_{jk}^{schl}. Such an effect would suggests math mentors play a key role in revealing exceptional math talent. While the data I use for the later analyses prevent me from decomposing this effect into recruitment, selection, and improvement, those mechanisms are still helpful for understanding how such an effect could occur.

Second, I am interested in the impact of these mentors on the later-in-life outcomes of individual exceptional math students. While later-in-life student outcomes are absent from this section, this framework does suggest some mechanisms through which mentors may effect such later outcomes. The most explicit is that math mentors may help exceptional math students acquire acquire credible signals of their their math ability (a^*_{ijk}). These signals may strengthen students' college applications, which help them attend more highly resources universities. These signals may also encourage further investment in these students' education by these parents, mentors, and/or the students themselves who are inspired to continue their success. More subtly, by organizing math clubs and competitions and recruiting students, these math mentors may cultivate an environment at their schools where excellence in mathematics is considered "cool" and positive peer effects are abundant. It seems reasonable to believe such an environment could have influence long-term outcomes.

B Robustness of Difference-in-Differences Estimates

In this Appendix I provide the tables and figures from the the robustness checks from Section 5.1.

B.1 Tables

	(1)	(2)	(3)
Mentor	0.348***	0.342***	0.245***
	(0.0605)	(0.0585)	(0.0531)
Free Lunch Share	-1.962***	-1.024***	-0.622*
	(0.258)	(0.275)	(0.349)
Mentor × Free Lunch Share	2.692***	1.805***	1.181***
	(0.298)	(0.304)	(0.293)
City Pop. (log)	0.267***	0.186***	-0.0272
	(0.0156)	(0.0156)	(0.0475)
City BA Share	11.21***	7.477***	5.214***
	(0.384)	(0.377)	(1.114)
City Income (per capita)	-0.0531***	-0.0348***	-0.0384***
	(0.00413)	(0.00399)	(0.0105)
School Enrollment (log)	1.329***	0.838***	0.951***
	(0.0507)	(0.0521)	(0.105)
Asian Student Share	3.210***	3.030***	4.485***
	(0.184)	(0.174)	(0.362)
Year FE	Yes	Yes	Yes
Schl FE	No	No	Yes
Technique	NB	NB	NB
Mean	0.245	0.660	0.660
N	33041	12238	12238
Log-Likelihood	-11638.7	-10499.4	-8119.5

Standard errors in parentheses

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

Table B.1: This table presents coefficients from Equation 6 estimated using negative binomial regression and the high school entry Math League sample. The coefficients of interest are those associated with Mentor and Mentor X Free Lunch Share, which capture the impact of high school Math League mentors on the number of top AMC scorers at a school in log odds and differential effects by schools' share of free lunch eligible students. The estimated coefficients provide evidence that Math League mentors increase the number of top AMC scorers at schools and have a larger, proportional, effect at disadvantaged schools. Standard errors are clustered at the school level.

	Middle Schools		High Schools	
	OLS	Poisson	OLS	Poisson
Mentor	0.215***	0.720***	0.108***	0.346***
	(0.0182)	(0.0359)	(0.0129)	(0.0318)
Free Lunch Share	-0.0588	-1.214***	0.0608	-0.401
	(0.0511)	(0.277)	(0.0450)	(0.271)
School Enrollment (log)	0.214***	1.695***	0.0964***	1.080***
	(0.0326)	(0.107)	(0.0303)	(0.107)
Asian Student Share	11.57***	6.832***	6.520***	5.315***
	(0.219)	(0.288)	(0.217)	(0.317)
Year FE	Yes	Yes	Yes	Yes
Schl FE	Yes	Yes	Yes	Yes
Technique	OLS	PN	OLS	PN
Mean	0.173	0.716	0.245	0.660
N	34766	8414	33041	12238
Log-Likelihood	-48351.1	-6027.1	-37694.1	-8464.1
AIC	96770.3	12120.2	75456.2	16994.2
BIC	97057.8	12352.4	75742.0	17238.8

Standard errors in parentheses

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

Table B.2: This table presents coefficients from Equation 3 estimated using OLS and Poisson for the middle school and high school entry Math League samples. The coefficients of interest are those associated with Mentor, which capture the impact of middle school Math League mentors on the number of top AMC scorers at a school in log odds. The estimated coefficients provide evidence that Math League mentors increase the number of top AMC scorers at schools. These estimates are consistent with those obtained using the original negative binomial regression approach, which strengthens the validity of the effects. Standard errors are clustered at the school level.

	Middle Schools		High Schools	
	Inflate	Count	Inflate	Count
Mentor	-1.176***	0.148	-0.661***	0.340***
	(0.144)	(0.119)	(0.102)	(0.0880)
City Pop. (log)	-0.142**	0.196***	-0.0930	0.244***
	(0.0604)	(0.0529)	(0.0570)	(0.0484)
City BA Share	-4.298***	6.539***	-8.727***	4.702***
	(1.507)	(1.248)	(1.391)	(0.992)
City Income (per capita)	0.0127	-0.0124	0.0399***	-0.0160*
	(0.0127)	(0.00779)	(0.0155)	(0.00897)
Free Lunch Share	3.498***	2.700***	0.771	-0.556
	(0.631)	(1.037)	(0.723)	(0.854)
School Enrollment (log)	-0.702***	0.522**	-0.884***	0.639***
	(0.147)	(0.224)	(0.158)	(0.149)
Asian Student Share	-2.204***	2.214***	-2.351***	1.810***
	(0.471)	(0.400)	(0.593)	(0.460)
Year FE	Yes		Yes	
Schl FE	No		No	
Technqiue	ZIP		ZIP	
Mean	0.173		0.245	
N	34766		33041	
Log-Likelihood	-7985.4		-11930.3	

Standard errors in parentheses

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

Table B.3: This table presents coefficients from Equation 3 estimated using zero-inflated, poisson (ZIP)for the middle school and high school entry Math League samples. The coefficients of interest are those associated with Mentor, which capture the impact of middle school Math League mentors on the number of top AMC scorers at a school in log odds. These estimates are consistent with those obtained using the zero-inflated, negative binomial (ZINB) regression approach, which strengthens the validity of the effects.

	(1)	(2)	(3)
Mentor	0.0627	-0.0600	-0.0450
	(0.0650)	(0.0690)	(0.0535)
City BA Share	13.71***	6.759***	-1.625**
	(0.426)	(0.395)	(0.643)
City Income (per capita)	-0.0458***	-0.0274***	-0.0229***
	(0.00371)	(0.00324)	(0.00515)
Free Lunch Share	-1.918***	-1.272***	-1.697***
	(0.155)	(0.194)	(0.217)
School Enrollment (log)	0.950***	0.339***	0.764***
	(0.0368)	(0.0436)	(0.0737)
Asian Student Share	2.909***	2.825***	7.604***
	(0.243)	(0.229)	(0.402)
Year FE	Yes	Yes	Yes
Schl FE	No	No	Yes
Technique	NB	NB	NB
Mean	0.0470	0.428	0.428
N	207065	22746	22746
Log-Likelihood	-19508.7	-14768.4	-11001.1

Standard errors in parentheses

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

Table B.4: This table presents estimated coefficients from a placebo exercise using the middle school never Math League sample. In this placebo exercise, I randomly assign the mentor treatment indicators from a school in the entry Math League sample to each school in the never Math League and estimate Equation 3 using the modified never Math League sample. While the estimated covariate coefficients are similar to those from the middle school entry Math League sample, the mentor effects are null. This provides evidence the positive, statistically significant, non-placebo estimated mentor effects are not the result of spurious correlations. Standard errors are clustered at the school level.

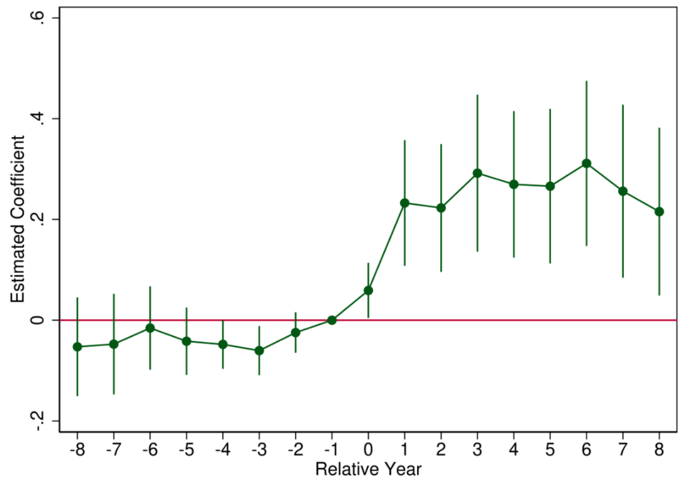
	(1)	(2)	(3)
Mentor	-0.0809**	-0.0437	-0.0183
	(0.0401)	(0.0401)	(0.0395)
City BA Share	11.49***	6.250***	3.931***
	(0.319)	(0.296)	(0.813)
City Income (per capita)	-0.0441***	-0.0223***	-0.0306***
	(0.00338)	(0.00302)	(0.00724)
Free Lunch Share	-2.390***	-1.927***	-1.222***
	(0.140)	(0.155)	(0.214)
log_students	1.252***	0.395***	0.881***
	(0.0308)	(0.0327)	(0.0728)
Asian Student Share	1.948***	1.518***	1.651***
	(0.175)	(0.159)	(0.517)
Year FE	Yes	Yes	Yes
Schl FE	No	No	Yes
Technique	NB	NB	NB
Mean	0.0415	0.281	0.281
N	220734	32610	32610
Log-Likelihood	-22427.5	-18056.5	-13349.4

Standard errors in parentheses

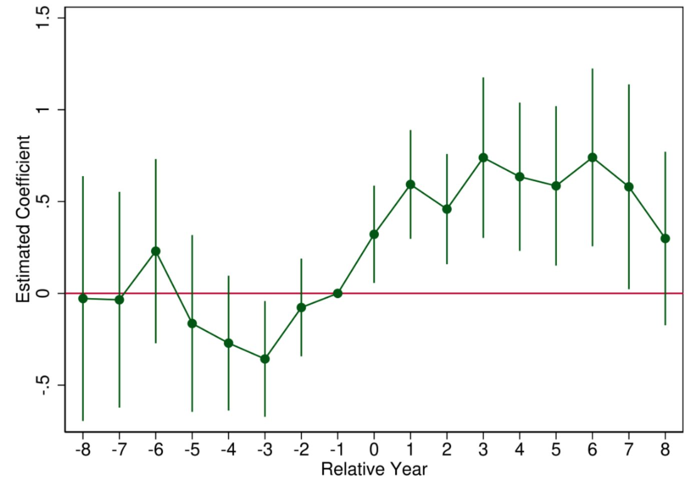
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.5: This table presents estimated coefficients from a placebo exercise using the middle school never Math League sample. In this placebo exercise, I randomly assign the mentor treatment indicators from a school in the entry Math League sample to each school in the never Math League and estimate Equation 3 using the modified never Math League sample. While the estimated covariate coefficients are similar to those from the middle school entry Math League sample, the mentor effects are null. This provides evidence the positive, statistically significant, non-placebo estimated mentor effects are not the result of spurious correlations. Standard errors are clustered at the school level.

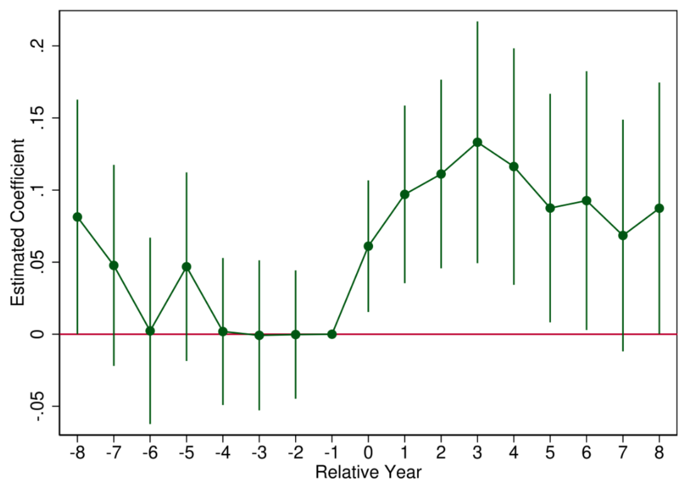
B.2 Figures



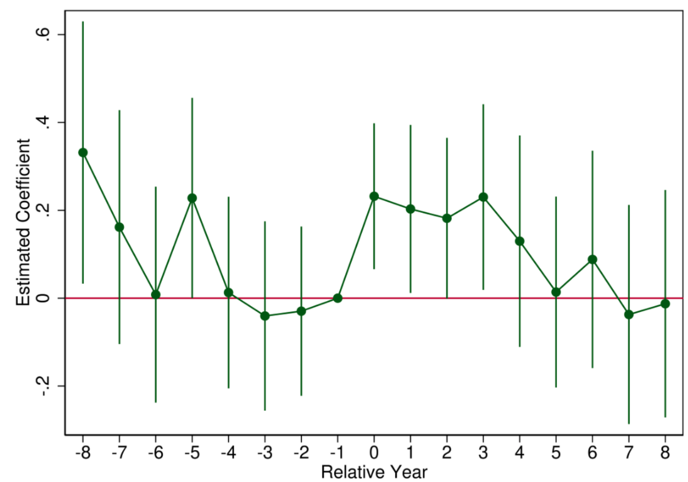
(a) OLS: Middle School



(b) Poisson: Middle School



(c) OLS: High School



(d) Poisson: High School

Figure B.1: These figures display the OLS and Poisson estimated event study coefficients from Equation 4 with 95% confidence intervals. The relative year coefficients are centered on the first year a school had a Math League mentor. School fixed effects are included for these models and standard errors are clustered at the school level.