

Early Mentors for Exceptional Students*

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Abstract

Although we are acquainted anecdotally with extraordinary 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; Airoidi 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 this 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 that 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 combine two complementary research designs to show the impact these mentors have on the later-in-life outcomes of students. I find these mentors greatly increase the probability that exceptional math students attend selective universities, major in STEM, earn PhDs, and pursue research careers. I then show that there are many “missing” exceptional math students who would have been revealed in high school if mentors were more widely available.

I use novel data from two mathematics competitions: one to identify exceptional math students—

the American Mathematics Competitions (AMC)—and another to identify math mentors—Math League. 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 publishes 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 online since 2010 and in printed booklets prior to that, 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. For this reason, I collected administrative data from another national math competition called Math League. The Math League data allow me to identify individuals—overwhelmingly math teachers—who organized math competitions at thousands of 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 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 (i.e. proficient mentors) 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 encouraged to take up such a role. For the exceptional math students, I use these data to observe later-in-life outcomes that math mentors might influence such as 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 exceptional math students identified by the AMC:

- **Fact 1:** Exceptional math students are disproportionately involved in science, innovation, and entrepreneurship.
- **Fact 2:** Even within the group of exceptional math students, those with higher AMC scores are more likely to attend selective universities, major in STEM fields, earn PhDs, and pursue

careers as a scientists, researchers, and academics.

- **Fact 3:** Even among exceptional math students with similar AMC scores and secondary school experiences, students from certain demographic groups are less likely to attend selective universities and major in STEM fields.

The first and second facts highlight the role exceptional math students in science and research. This 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 exploiting plausibly exogenous variation in the timing with which 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 248%. For high schools this effect is smaller, but still very large (110%).¹ 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 identifying and nurturing exceptional talent at schools than it has been in the past.

I provide credibly causal evidence that high school math mentors have a statistically significant effect on the later in life outcomes of exceptional math students. This analysis focuses on 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 that their having a math mentor in high school increases the probability of their attending a 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 control for middle school fixed effects and a measure of students' 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. A comparison between the OLS estimates and IV estimates indicate that mentors' effects are especially large for students whose experience of a mentor depends on idiosyncratic mentor availability

¹The size of the effects immediately suggests, first, that AMC high scorers are indeed very rare and, second, that the mentors are identifying latent exceptional students, not primarily producing gains through instruction from which any student could benefit.

(compliers). In the case of attending a 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 simply because their school did *not* participate. My estimates indicate that at these schools around 55% 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 or opportunities relevant to these students may be related to population concentration.

I use results from the aforementioned analyses to provide counterfactual estimates for the impact of math mentors on the later-in-life outcomes of the missing exceptional math students. These estimates suggest that increasing access to math mentors would dramatically increase the number of exceptional math students who attend selective universities, major in STEM fields, earn PhDs, and pursue research careers. Expanding access to realize these gains appears possible for a few reasons. First, the financial (out-of-pocket) cost of offering the AMC or Math League is *extremely* modest. Second, the descriptive evidence shows that the typical mentor did not graduate from a selective college and is paid little or nothing for mentoring, meaning there may be many math teachers who could fulfill this role.

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 environments 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 wealth in determining who becomes an inventor or knowledge producer later in life (Morgan et al., 2022; Hoisl, Kongsted and Mariani, 2023; Airolidi and Moser, 2024; Novosad et al., 2024). My paper advances this literature in two

important ways. First, I provide causal evidence for an often hypothesized mechanism 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 dataset of exceptionally talented math students from diverse backgrounds that can be used for future 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 that high-achieving students attend selective universities.

My research also contributes to the literature in economics and developmental psychology that examines the impact of natural (non-parental) mentors on children’s development (Beam, Chen and Greenberger, 2002; Zimmerman, Bingenheimer and Behrendt, 2005; Miranda-Chan et al., 2016; Raposa et al., 2018; Fruht and Chan, 2018; Hagler and Rhodes, 2018; Van Dam et al., 2018; Gowdy and Spencer, 2021; 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 even students who are exceptionally gifted benefit from natural mentorship.

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):

$$T = AC^\alpha \underbrace{(p_p N_p)^\beta}_{\text{proficient mentors}} \underbrace{(p_e N_e)^\gamma}_{\text{expert mentors}} \quad (1)$$

where, because expertise is scarce, $N_e \ll N_p$, 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 much smaller 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 might be 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

To test the proficient mentor hypothesis, I need a large, geographically and temporally diverse sample of exceptional math students, along with information about their middle schools, high schools, potential exposure to 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 data from the flagship middle school competition (AMC 8) and flagship high school competitions (AMC 10 A/B and AMC 12 A/B).²³ The data contain summary statistics for these competitions as well as various lists of high-scoring students. The summary statistics provide details on the number of participating schools, participating students, and competition score distributions. 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.⁴ In most years, scoring in the top 3,200 is sufficient to make the student honor roll lists. 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. Such information is crucial for understanding how access to math mentors and extracurricular activities might vary across 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 include information on all participating schools, the individuals at these

²The data also cover the American Invitational Mathematics Examination (AIME) and the United States American Mathematical Olympiad (USAMO).

³The AMC has changed the names of these competitions over the years. From its inception in 1985 until 1999, the 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 changed 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.

⁴The 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.

schools who facilitate these competitions, and the names of top-performing students.

These Math League data are necessary for my analyses for a few 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 schools' participation. Knowing exactly when these competitions are offered is necessary for my later empirical strategies because they allow me to determine when a math mentor is active at a school. Second, the information on the school employees who organize Math League competitions allows me to match the math mentors with other data on their qualifications and careers. 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 allows me to identify students who demonstrated exceptional math ability in middle school, but did not participate in Math League during high school.

3.3 LinkedIn Data

I use data from LinkedIn (via Revelio Labs), which include online professional profiles of over 700 million individuals, to track the later-in-life outcomes of students in the AMC data. From these profiles, I observe names and self-report information on educational and employment history. Revelio Labs also imputes gender and race for these LinkedIn profiles based on names and user location, which I use 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 selective university, majoring in a STEM field, earning a PhD, and starting their research career (i.e. having a position as a scientist, researcher, or professor).

3.4 Supplementary Education Data

I obtained 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 1989.⁵

⁵Per 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."

The CCD and PSS data provide information on school names, geographic locations, grades offered, student enrollment and demographic counts, and faculty employment.⁶⁷ I match the schools in the AMC and Math League data to these sources using the school name and location information. The NCES data provide important information on the school characteristics 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.

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 (e.g. teacher, gifted & talented coordinator, principal), their teaching experience, and the timing of their 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 key facts that would be challenging to derive using data from common standardized tests like ACT/SAT, 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 exceptional 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 using additional information to estimate the probability that a potential match leads to an exact first name match.

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 a LinkedIn profile of a US college graduate from the same graduating cohort with the same gender. 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

⁶For private school data in odd number years, I simply use PSS data from the previous even number year.

⁷Based 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.

selection onto LinkedIn.

Although the descriptive patterns and takeaways are largely consistent between the middle school and high school matched samples, there are 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 could not serve as a substitute. For brevity, when reporting analogous statistics or referencing similar tables and figures 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 selective universities (22%/31%), major in STEM (48%/54%), earn PhDs (8%/12%), and pursue research careers (8%/11%) at very high rates (Table 1a and Table B.1a). Compared to the matched reference sample, the middle school AMC students are eleven times as likely to attend a selective university, twice as likely to major in STEM, four times as likely to earn a PhD, and three times as likely to pursue a research career. A notable demographic difference between the AMC samples and the reference samples is that the AMC sample has a higher share of Asian and Pacific Islander (Asian/PI) 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 (3%/4%). Many of the students in these majors earn PhDs and pursue careers as scientists, researchers, and professors (Table 1b and Table B.1b).

Ultimately, the economic and scientific impacts of these students depend on their career decisions and opportunities after college. From Tables 1a and B.1a, it is clear these students pursue research careers at a relatively high rate. These statistics and estimates, however, do not fully communicate the unique economic and scientific contributions of these students.

To better demonstrate the role these students play in the economy, I perform a text analysis on the job titles and company names they list on their LinkedIn 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 repeat this for the reference sample. The frequencies from the two reference samples help 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.

Comparing the word frequencies between the AMC and reference samples reveals that top AMC students pursue impressive careers in a diverse set of fields. These AMC students work in academia, science, technology,⁸ medicine, and finance at rates much higher than other college graduates found on LinkedIn. The list of company names confirms these AMC high scorers are disproportionately employed by the most innovative and prestigious companies and universities in the world (Table 2 and Table B.2).

Fact 2: Even within the group of exceptional math students, those with higher AMC scores are more likely to attend selective universities, major in STEM fields, earn PhDs, and pursue careers as scientists, researchers, and academics.

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 math ability at this level (Ellison and Swanson, 2010). Yet, relative AMC performances continue to have predictive power beyond this range of ability for important later-in-life outcomes even after controlling for student gender, race, high school graduation year, and school fixed characteristics (Figure 2 and Figure B.1).

To estimate the relationship 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,⁹ high school graduation cohort fixed effects (τ_t), and school fixed effects (δ_s). I multiply the AMC ranks by -1,000 so the coefficient on $rank_i$ corresponds to an improvement in AMC rank by 1,000 positions.

$$y_i = \alpha + \beta rank_i + \gamma_t + \delta_s + X_i \lambda + \epsilon_{ist} \quad (2)$$

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.

⁸The 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)

⁹e.g. 2008 AMC 10 A.

The estimates indicate that a 1,000 rank improvement in AMC performance is associated with a 2.3pp/1.3pp higher probability of attending a 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 pursuing a research career. The estimates are all highly statistically significant.

Fact 3: Even among exceptional math students with similar AMC scores and secondary school experiences, students from certain demographic groups are less likely to attend selective universities and major in STEM fields.

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

The gender gaps are the particularly 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 such a large gap among exceptionally talented male and female students despite rich controls is surprising (Niederle and Vesterlund, 2010; Buser, Niederle and Oosterbeek, 2014; Niederle, 2017; Cimpian, Kim and McDermott, 2020; Card and Payne, 2021). 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 at which these male and female students attend selective universities. According to the estimates, female students are 4pp/6pp less likely to attend selective universities. 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). In Figure 3a, I use a binned scatterplot (with controls) to show that, while there is a strong positive relationship between high school AMC rank and selective university attendance for male students, no such relationship exists for female students. This raises concerns that female math talent is not being sufficiently nurtured and encouraged. This pattern holds for most of the outcomes of interest (Figure B.2).

The school fixed effects obscure important childhood environment inequalities that limit access to selective universities. In Figure 3b, I use a binned scatterplot to show that there is a strong positive relationship between the share of college graduates in a top AMC student's high school city and the probability that the student attends a selective university even after controlling for AMC rank and many other factors. This suggests that even at this extreme level of ability, exceptional math students from less educated areas face barriers in accessing resources well-matched to them. Interestingly, there is not a positive relationship between this college graduate share and any of the other outcomes of interest (Figure B.3). Indeed, there appears to be a negative relationship between college graduate share and majoring in STEM, which is driven by AMC students from cities with very high shares of college graduates (> 40%).

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. For 257 of these unique mentors I can observe their first year as a Math League mentor.

In Table 4a, I provide information on the demographic characteristics, education, and work experience of these 257 individuals during their first year as math 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. On average, these mentors organize Math League for 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 as a mentor for Math League or for a similar program. To provide further evidence of this, I link mentors from the Math League data to their LinkedIn profiles. I match on first name, last name, and school.¹⁰ I provide summary statistics for these mentors in Table 4b. 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 credibility that math teachers who could be school-based mentors to exceptionally talented students might be abundant.¹¹

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

¹⁰Individuals 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.

¹¹I cross-referenced these matched mentors samples with the AMC data to see whether the mentors were themselves top AMC scorers in high school. I found very few potential matches (< 3% of those who graduated high school after 1980).

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 and use 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 of Math League 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 schools that first had a Math League mentor between 1994 and 2020. I begin by identifying all public non-charter, non-magnet 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 first becomes active. I refer to this sample as the *entry* Math League sample.

In Table 5a, 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 of schools 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 5b. 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/PI students, and lower shares of economically disadvantaged students. These samples also differ 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 a few 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.¹² 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 have more than 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 a high degree of overdispersion.¹³ 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 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/PI, White, Black, and Hispanic students), and the share of economically disadvantaged students:

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

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

¹²I 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.

¹³Ellison & 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.

and AMC performance.

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

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

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 $I[t = k + T_s^{(entry)}]$. 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 estimated coefficients imply Math League mentors have an enormous impact on the amount of exceptional math talent discovered at schools (Table 6). They indicate mentors increase the number of top AMC scorers at middle schools by 248% and at high schools by 110%. In the specification including school fixed effects, the implied effects are still very large (165% and 47%, respectively).

In Figure 4, 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 were 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 then 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 suggests 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 students. 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, and encourage participation in the AMC. The estimated mentor effect on revealed talent is 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 universally available 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.¹⁴

This directly relates 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.

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 many top AMC 12 scorers school s in year t would produce if the school *did* participate in 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 probability of participation and the talent estimate:

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

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 amount of exceptional talent at a school \widehat{talent}_{st} . If the estimated increase in revealed talent were being entirely driven by schools going from zero to positive counts in response to the mentors, then the estimated mentor effect would be significant for the inflate portion of the model and zero for the count portion. In contrast, if the estimated increase in revealed talent were being entirely driven by schools already participating in the AMC going from positive counts to higher positive counts, then the opposite would be true.

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 as I did for the negative binomial estimation.

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 stock of actual talent (Table 6). 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

¹⁴AMC participation can only be confirmed for schools that have *at least one* top scorer.

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 revealed at schools already participating in the AMC 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 5).

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 school-based mentors influence the amount of revealed talent at a school is offered in Appendix A.

5.1.1 Heterogeneous Effects and 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} :

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

The model is otherwise identical to Equation 3.

The estimates indicate the mentor effects are actually larger for more disadvantaged schools (Table C.1 and Table C.2). The estimates from the negative binomial model with school fixed effects indicate that relative to a high school with no free lunch eligible students, the mentor effect at a high school where 20% of the students are free lunch eligible is 95% larger. This is even more dramatic for middle schools. 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 at more disadvantaged

schools, while more advantaged schools are more likely to be participating during the pre-period.¹⁵

To provide evidence that my results are robust to alternative functional form assumptions, I repeat the analysis using OLS, Poisson, and zero-inflated Poisson (ZIP). The estimated mentor effects for these models are provided in Tables C.3 and C.4. The OLS estimates suggest mentors increase the number of top AMC scorers by 0.215 students at middle schools and 0.108 students at high schools; relative to the mean of top AMC counts, these effects are large. The coefficients estimated 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 C.1).

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 C.5 and Table C.6). These results suggest that the original estimated mentor effect on the number of top AMC scorers is unlikely to be driven by spurious 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 misspecified 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 sub-

¹⁵Another 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 schools are more motivated than their peers at advantaged schools—they may have to overcome more institutional barriers to organize such programs—and those in the sample are particularly talented at revealing and fostering talent.

sample 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 later¹⁶.

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 24 Math League exams available to them in high school should be relatively easy. Consequently, this serves a good proxy for Math League participation for these exceptional students. 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 student’s middle school was within 5 miles of a high school that offered Math League during the years the student was in high school.¹⁷

I compare students who do and do not have a high school Math League mentor in Table 7. Pre-high school characteristics, such as middle school AMC performance and demographics, are fairly similar for students who 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 school district fixed effects (σ_s).

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

¹⁶Based on the grade reported in the AMC data.

¹⁷In 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.

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 based on the city of the middle school are also included as controls (income per capita, logged population, and share of college graduates based on the 2000 census). I also use school district fixed effects to help control for unobservable time-invariant differences in school district 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 8). The estimates 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, perhaps, increases their enthusiasm for STEM or education more generally. This signal and an informed reference letter from the mentor helps the student be admitted to a highly resourced technical school like MIT. At MIT the student is encouraged to continue pursuing STEM and has more exposure to researchers. This exposure encourages them to earn a PhD and/or pursue a research career.

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 differences in students’ enthusiasm for mathematics that exist despite their shared middle school math competition engagement and success. 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 this, 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 ($mentor_i$). Under the identifying assumptions, the estimates generated using this IV strategy capture the causal effect of mentors on the compliers—the exceptional math students who are induced to participate in Math League by the availability of a mentor.

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, ensuring that 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.

I estimate the IV coefficients using two-stage least squares regression:

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

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

For the first stage I regress $mentor_i$ on $exposure$ while including all the controls from before (Equation 8). 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 9). 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 ($mentor = 1$) compared to 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 are much larger than the OLS estimates (Table 8). 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 use 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 if they had had a mentor.

6.1 Model Validation for Out-of-Sample 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, $\text{talent}_{st}^{(r)}$. For all the school-year observations in this sample $\text{mentor}_{st} = 0$, 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} (Equation 5).

The summary statistics for the *never* Math League high school sample used in this analysis and *entry* Math League high school sample—which first joined Math League between 1994 and 2020—are provided in Table 5b. As stated before, the samples differ in some important ways: the schools used to estimate the model have higher shares of white and Asian/PI students, lower shares of economically disadvantaged students, and tend to be located in more affluent and college educated areas. 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 for the never Math League high schools—schools that were not used in the original estimation of the model—when viewed in aggregate. 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 6a). This suggests the estimated model is performing well for schools of various types, though the model appears 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 (Figure 6b).

The realized counts fall quite short for some states like Hawaii, Idaho, Oklahoma, and Wyoming. 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 over the same 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.¹⁸ 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.¹⁹ With the Hawaiian schools dropped, the average overestimate is a modest 7.2%.

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 never Math League high schools produce using the estimated high school ZINB model, but now assert that $mentor_{st} = 1$ for all schools and time periods. Under this scenario, these 8,160 schools²⁰ 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 students 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 (Figure 7).

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 8). Based on this exercise, these mentors would have

¹⁸Hawaii is the only US state that is majority Asian/PI, and the share of Asian/PI students at Hawaiian high schools reflects this. The ZINB model, which is estimated on schools with comparatively low shares of Asian students (Table 5), finds the share of Asian students is a key predictor for both the inflate and count estimates. Together, these two facts produce the overestimates.

¹⁹For 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.

²⁰Recall I dropped 33 schools from Hawaii.

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 research careers (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. Even with the descriptive evidence on mentors suggesting they might be abundant, this seems 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 one 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 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 expanding 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

Table 1: Summary of AMC-LinkedIn Matched Samples

(a) Summary Statistics for Top AMC Students (High 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
Asian/PI	0.25	0.43	0.08	0.27
Other Race	0.07	0.26	0.18	0.38
HS AMC Rank	2,382.07	1,644.69	.	.
Selective University	0.31	0.46	0.02	0.15
Math Major	0.14	0.34	0.02	0.13
STEM Major	0.54	0.50	0.21	0.40
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) Majors of Top AMC Students (High 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		

These tables provide summary statistics for the high school AMC-LinkedIn matched samples. In Table 1a, I compare top AMC students to a random reference sample of LinkedIn users. To construct the reference sample, I matched every top AMC student in the high school AMC-LinkedIn matched sample to another college graduate of the same gender who graduated in the same year. Comparing the two samples highlights important differences between top AMC scorers and the average college graduate found on LinkedIn. In Table 1b, I examine the majors pursued by top AMC scorers. The first column of this table displays the share of the students in the high school AMC-LinkedIn matched sample who major in a given subject (double majors counted twice). The second column provides the rate that the students within a given major pursue a PhD. The final column lists the average AMC rank of students in the sample with a given major; the majors are sorted by these AMC rank averages.

Table 2: Careers of Top AMC Students (High School)

(a) Job Titles				(b) Employers			
Job Title Word	AMC Sample	Ref. Sample	Ratio	Job Location	AMC Sample	Ref. Sample	Ratio
cofounder	83	1	83	microsoft	38	0	.
cs	112	2	56	apple	25	0	.
quantitative	68	5	13.6	meta	22	0	.
physics	45	4	11.3	mit	17	0	.
phd	167	15	11.1	epic	15	0	.
mathematics	62	7	8.9	intel corporation	14	0	.
trader	61	7	8.7	jane street	11	0	.
math	70	9	7.8	capital one	11	0	.
researcher	105	14	7.5	mckinsey & company	10	0	.
scientist	252	34	7.4	kaiser permanente	10	0	.
machine	52	7	7.4	harvard medical school	9	0	.
professor	281	43	6.5	uiuc	9	0	.
fellow	97	16	6.1	boeing	9	0	.
software	862	158	5.5	nvidia	9	0	.
sr	117	22	5.3	google	130	3	43.3
resident	95	18	5.3	amazon	39	1	39
physician	117	28	4.2	facebook	29	1	29
data	303	74	4.1	stanford university	26	1	26
computer	112	27	4.1	harvard university	18	1	18
learning	73	18	4.1	university of washington	14	1	14
research	239	67	3.6	princeton university	14	1	14
science	178	50	3.6	university of chicago	13	1	13
candidate	116	34	3.4	university of california berkeley	13	1	13
engineer	1375	414	3.3	cornell university	12	1	12
analytics	90	28	3.2	northwestern university	12	1	12

These tables provide insight on the careers of students in the high school AMC-LinkedIn matched sample. Table 2a provides information on words appearing in the job titles of these students. The second column in this table reports the number of AMC students out of 10,000 students whose primary job title on LinkedIn includes the listed word. The third column shows the same frequency for the reference sample. The listed words are those that show up in the profiles of at least 0.5% of the AMC sample and have the highest frequency ratios. Table 2b provides information on employers of the AMC students. The second column in this table reports the number of AMC students out of 10,000 students who put the listed employer as their primary employer on their LinkedIn profile. The third column shows the same frequency for the reference sample. The listed employers are those that show up in the profiles of at least 0.1% of the AMC sample and have the highest frequency ratios. Both tables are sorted by the ratio between the AMC sample and reference sample frequencies. Together, these tables demonstrate top AMC students pursue highly quantitative careers in a variety of different fields and industries.

Table 3: Descriptive Regression Estimation

	Selective University	STEM Major	PhD	Research Career
HS AMC Rank	0.0134*** (0.00220)	0.0164*** (0.00240)	0.0125*** (0.00186)	0.00438** (0.00176)
Female	-0.0572*** (0.00753)	-0.198*** (0.00813)	-0.0214*** (0.00508)	-0.00796* (0.00453)
Asian/PI	0.0456*** (0.0102)	-0.00189 (0.00845)	-0.0315*** (0.00566)	0.0130** (0.00553)
Other Race	0.0435*** (0.0122)	-0.0188 (0.0133)	-0.0160* (0.00900)	-0.00402 (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

This table reports the OLS estimated coefficients for Equation 2 for a selection of outcomes. These coefficients are estimated using the high school AMC-Linkedin matched sample. The positive coefficients on AMC rank demonstrate that even among these exceptional math students, those who demonstrate greater mathematical ability on the AMC are more likely to have these later-in-life outcomes. The other coefficients demonstrate that gender and racial gaps in these outcomes persist even after controlling for ability—as demonstrated by AMC—and high school. Standard errors are clustered at the school level.

Table 4: Descriptive Evidence on Math League Mentors

(a) Wisconsin Mentor Matched Sample			(b) LinkedIn Mentor Matched Sample		
	mean	sd		mean	sd
Male	0.44	0.50	HS Cohort	1991.44	12.64
White	0.99	0.11	Male	0.44	0.50
Masters	0.44	0.50	White	0.90	0.30
PhD	0.00	0.00	Asian/PI	0.02	0.15
Teacher	0.91	0.29	Other Race	0.08	0.27
Math Teacher	0.84	0.37	University not Listed	0.53	0.50
Physics Teacher	0.02	0.15	Selective University	0.04	0.19
Comp. Sci. Teacher	0.04	0.18	Major not Listed	0.55	0.50
Principal	0.00	0.06	Education Major	0.09	0.28
G&T Coordinator	0.08	0.27	Math Major	0.30	0.46
Department Chair	0.04	0.20	STEM Major	0.36	0.48
Club Advisor	0.14	0.35	Masters	0.41	0.49
Athletic Coach	0.09	0.28	Education Masters	0.22	0.42
Total Teaching Experience	12.06	9.34	STEM Masters	0.12	0.32
District Teaching Experience	9.44	8.76	PhD	0.04	0.19
Recent Hire (Dist. Exp. ≤ 3)	0.32	0.47	Education PhD	0.03	0.18
School's First ML Mentor	0.19	0.39	STEM PhD	0.01	0.11
ML Mentor Years	3.50	3.38	Observations	1,972	
Observations	257				

These tables provide descriptive evidence on the mentors who organize Math League at high schools. Table 4a reports summary statistics for 257 Wisconsin Math League mentors during the first year they organize the activity. This information is collected from the Wisconsin All Staff data. In this sample, the vast majority of Math League mentors are math teachers. These mentors have an average of 12 years of teaching experience and organize the activity for 3.5 years. Table 4b reports summary statistics for 1,972 Math League mentors who are matched to their LinkedIn profiles. This sample suggests very few of these mentors attended selective universities like many of the top students they mentor do. The two samples are similar on observables shared between the samples. For those mentors I could feasibly observe in the AMC data I have collected, very few ($< 2\%$) were top AMC scorers in high school.

Table 5: Public School Samples by Math League Status

(a) Middle School

	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/PI 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
College Grad Share	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	

(b) High 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/PI 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
College Grad Share	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	221,211		33,102		33,075	

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. The first set of variables are from the National Center for Education Statistics, the second set are from the 2000 Census, the third set are from the Math League data, and the final set are from the AMC data.

Table 6: Mentor Effect on Revealing Talent

	Middle School				High School			
	NB		ZINB		NB		ZINB	
	(1)	(2)	(3) Inflate	(3) Count	(4)	(5)	(6) Inflate	(6) Count
Mentor	1.249*** (0.0808)	0.977*** (0.0576)	-1.271*** (0.175)	0.168 (0.113)	0.741*** (0.0425)	0.384*** (0.0399)	-0.876*** (0.206)	0.419*** (0.111)
Population (1000s, log)	0.292*** (0.0255)	0.0685 (0.0456)	-0.102 (0.0678)	0.237*** (0.0515)	0.265*** (0.0156)	-0.0229 (0.0472)	-0.0530 (0.0842)	0.222*** (0.0514)
Income per Capita (1000s)	-0.0380*** (0.00453)	0.0129* (0.00679)	0.0106 (0.0146)	-0.0163 (0.0112)	-0.0508*** (0.00411)	-0.0365*** (0.0105)	0.0496** (0.0230)	-0.0299*** (0.0108)
College Grad Share	11.84*** (0.617)	-2.989*** (0.996)	-2.915 (1.811)	8.052*** (1.573)	11.13*** (0.383)	5.100*** (1.111)	-8.426*** (2.748)	6.915*** (1.286)
School Enrollment (log)	1.062*** (0.0729)	0.756*** (0.131)	-0.575*** (0.212)	0.690*** (0.258)	1.335*** (0.0507)	0.951*** (0.105)	-1.293*** (0.281)	0.616*** (0.165)
Asian/PI Share	3.645*** (0.297)	2.521*** (0.333)	-1.625*** (0.534)	3.378*** (0.556)	3.069*** (0.184)	4.511*** (0.365)	-18.17*** (6.978)	1.233** (0.599)
Free Lunch Share	-1.132*** (0.293)	-1.665*** (0.358)	4.651*** (0.680)	3.958*** (0.759)	-0.822*** (0.214)	-0.0696 (0.317)	-0.395 (1.649)	-0.729 (0.999)
Year FE	Yes	Yes	Yes		Yes	Yes	Yes	
Schl FE	No	Yes	No		No	Yes	No	
Mean	0.173	0.716	0.173		0.244	0.660	0.244	
N	34,830	8,424	34,830		33,102	12,258	33,102	
Log-Likelihood	-7,653.0	-4,960.3	-7,300.5		-11,695.1	-8,138.7	-11,409.7	

This table presents coefficients from the difference-in-difference strategy outlined by Equation 3. These coefficients are estimated using negative binomial regression (NB) and zero-inflated, negative binomial regression (ZINB) with the entry Math League samples that are composed of schools that first start offering Math League between 1994 and 2020. The coefficients of interest are those associated with Mentor. The NB estimates capture the impact of 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 substantially. The ZINB estimates tests whether these effects are being driven by mentors expanding access to the AMC at the school-level or if these mentors are increasing the number of top AMC scorers at schools already participating. These are also given in log odds. The large, negative and highly significant coefficients from the inflate portion of the model suggest these mentors are introducing the AMC to many of these schools. The coefficients for the count portion of the model suggest these mentors are also increasing the number of top AMC scorers at schools that participated in the AMC before the mentor started organizing Math League; this effect is larger and more significant for the high school sample. Standard errors are clustered at the school level.

Table 7: Summary of Exceptional Math Students with and without High School Mentors

	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/PI/White	0.09	0.28	0.10	0.30
Population (1000s, log)	10.78	1.57	10.93	1.53
College Grad Share	0.28	0.11	0.31	0.12
Income per Capita (1000s)	30.27	12.60	34.57	14.25
MS AMC Rank	1,824.62	1,304.02	1,588.79	1,268.13
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 University	0.19	0.39	0.29	0.45
PhD	0.08	0.27	0.09	0.29
Research Career	0.09	0.29	0.11	0.32
Observations	7,192		1,527	

This table reports summary statistics on students from the middle school AMC-LinkedIn matched 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. The variable *Mentor Near MS* is an indicator for whether the middle school attended by the student was within five miles of a high school with a Math League mentor.

Table 8: Mentor Effect on Later-in-Life Outcomes

	Top HS AMC		Selective University		STEM Major		PhD		Research Career	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Mentor	0.157*** (0.0107)	0.340** (0.163)	0.0575*** (0.0124)	0.411** (0.194)	0.0376** (0.0153)	0.472** (0.239)	0.0217** (0.00849)	0.225* (0.131)	0.0171* (0.00924)	0.252* (0.143)
MS AMC Rank	0.0482*** (0.00192)	0.0456*** (0.00307)	0.0218*** (0.00222)	0.0167*** (0.00365)	0.0141*** (0.00274)	0.00780* (0.00450)	0.00678*** (0.00152)	0.00383 (0.00247)	0.00600*** (0.00166)	0.00260 (0.00270)
Mean	0.163	0.163	0.206	0.206	0.509	0.509	0.0794	0.0794	0.0938	0.0938
N	8,719	8,719	8,719	8,719	8,719	8,719	8,719	8,719	8,719	8,719
Adj. R-squared	0.160		0.0688		0.0741		0.0218		0.00322	

This table presents the OLS and IV estimated mentor effect from Equation 7 and Equation 9 for various student outcomes. The first stage for the IV is shown in Table 9. For each outcome of interest, the estimated mentor effects are statistically significant and positive, which provides evidence that mentors increase the probability of these outcomes. The IV estimates are substantially larger than the OLS estimates. This may be because the OLS estimates are biased downwards, or because mentors are especially influential on the students who are induced to participate in Math League by the presence mentors. Standard errors are clustered at the school level.

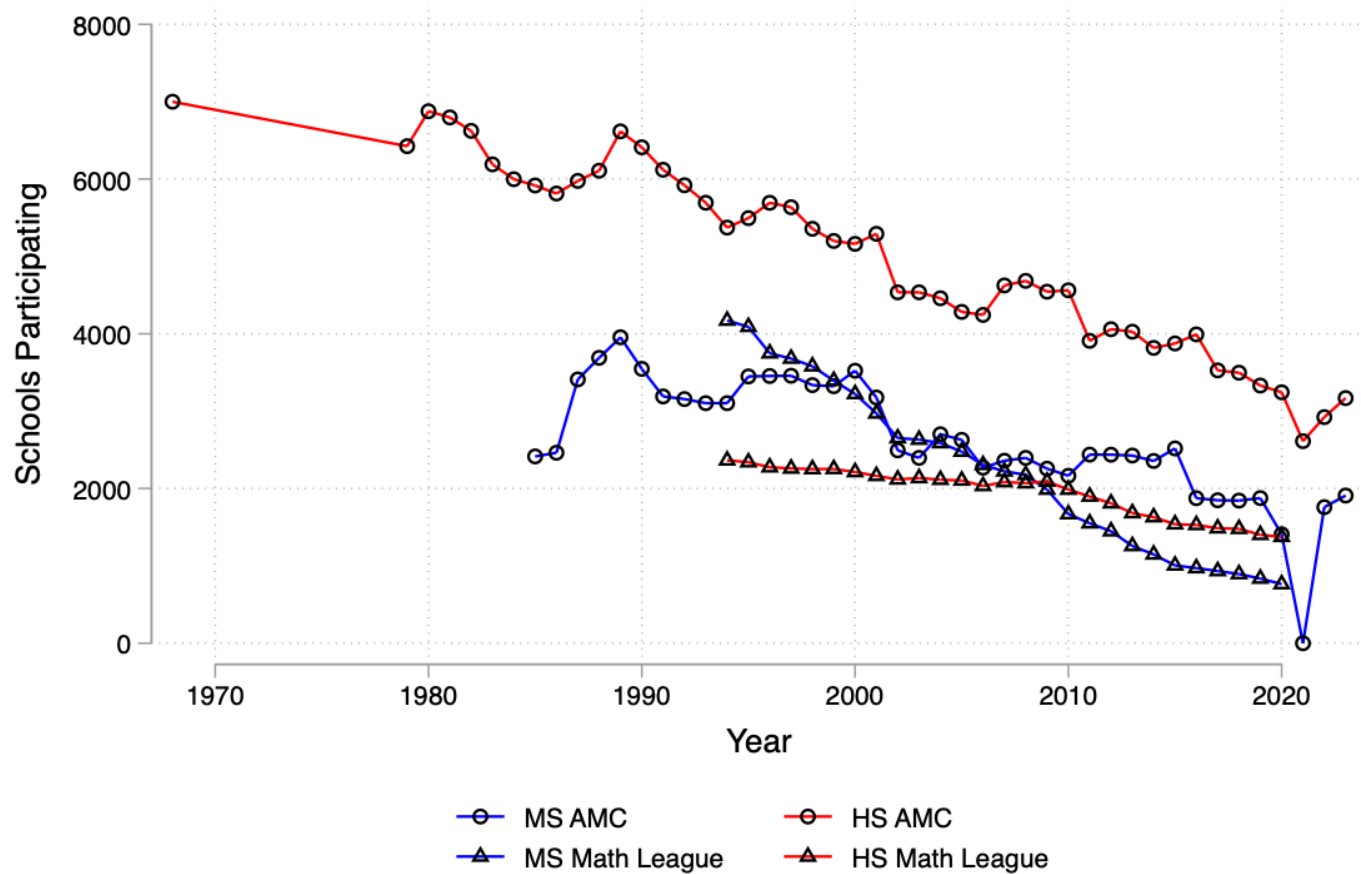
Table 9: Near HS Mentor Instrument (First Stage)

	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)
Other Race	0.00768 (0.54)
Mean	0.2123
N	8,719
F-Stat	35.78

This table shows 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. The coefficients on the covariates suggest mentor take up is slightly higher for students with better middle school AMC scores, Asian/PI students, and male students.

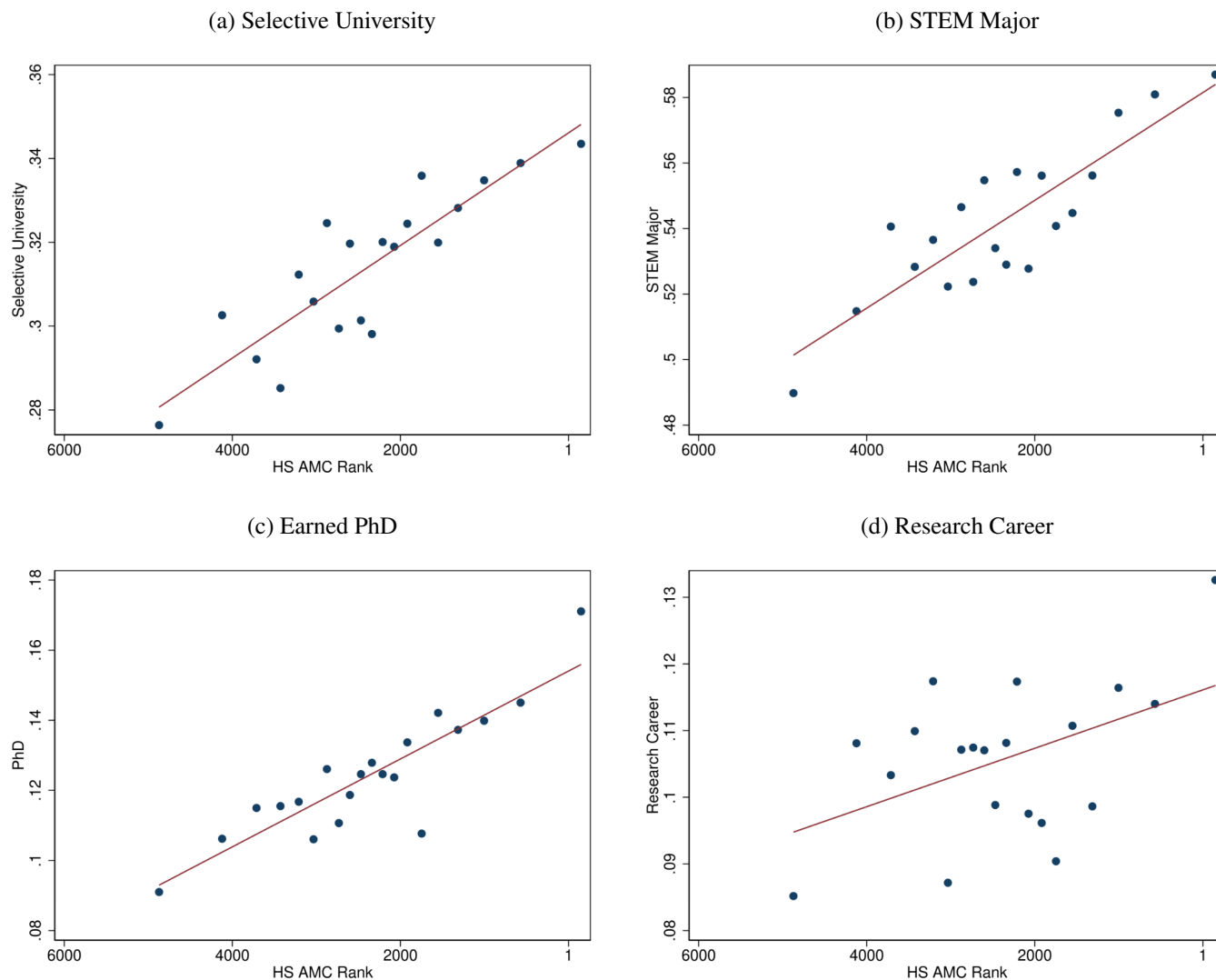
Figures

Figure 1: Decline in Math Competition Participation at US Schools



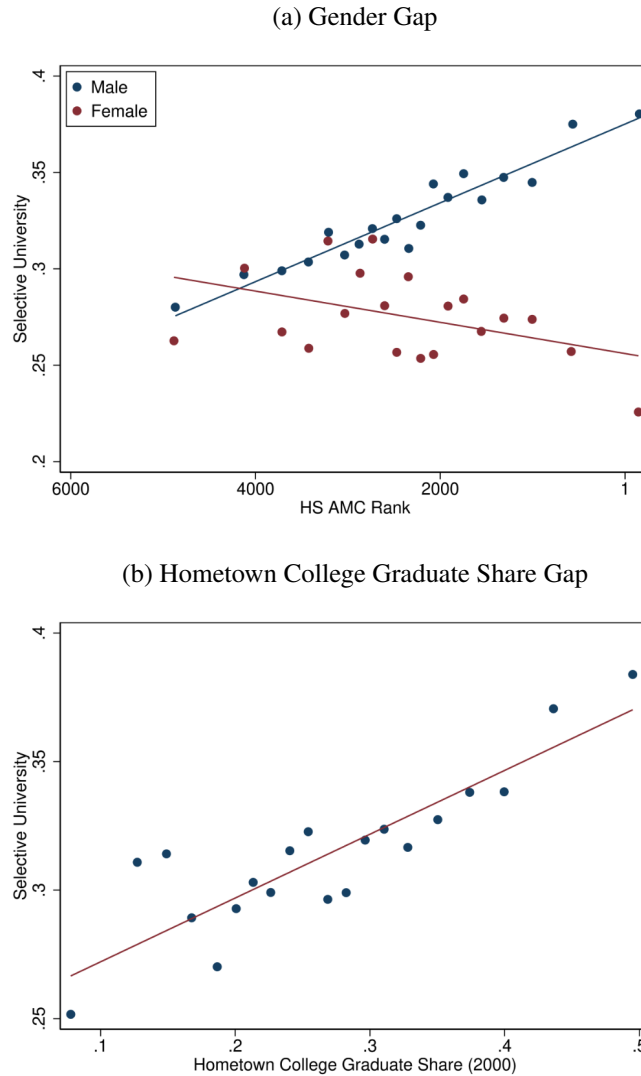
This figure shows the number of US middle schools and high schools participating in Math League and AMC competitions over time. The downward trend suggests an increasing share of the exceptionally talented math students in the US do not have mentor at their schools who is organizing these activities, despite their low costs (\$100 per school for Math League, \$184 per school for AMC). Declining participation is primarily driven by schools with higher shares of economically disadvantaged students.

Figure 2: High School AMC Rank vs Later-in-Life Outcomes



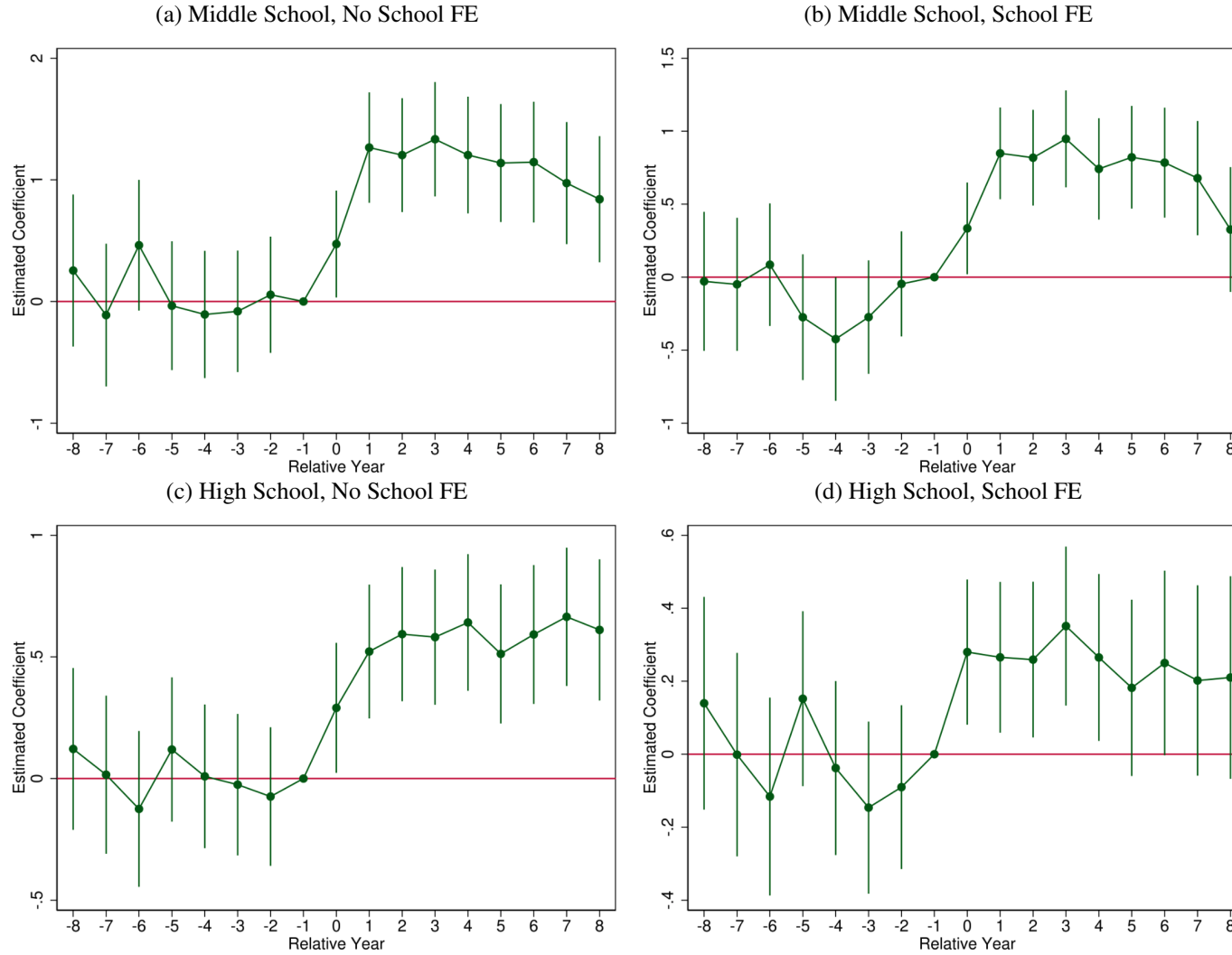
This figure displays a series of binned scatter plots between AMC 10/12 rank and later-in-life outcomes for students in the high school AMC-LinkedIn matched sample. These plots are constructed while controlling for student gender, race, high school cohort, high school fixed effects, test fixed effects (e.g. observation based on 2012 AMC 10 A), and grade fixed effects (e.g. observation taken while student was in 11th grade). These plots demonstrate there is a strong, positive relationship between high school AMC rank and later-in-life outcomes associated with knowledge production even after controlling for demographic and socioeconomic conditions.

Figure 3: Inequality in Selective College Attendance



These binned scatterplots highlight inequality in access to selective universities among top high school AMC scorers. Figure 3a displays the relationship between students' AMC 10/12 rank and selective college attendance by gender while controlling for student race, high school cohort, high school fixed effects, test fixed effects (e.g. observation based on 2012 AMC 10 A), and grade fixed effects (e.g. observation taken while student was in 11th grade). While there is a strong positive relationship between AMC rank and selective university attendance for male students, there is no such relationship for female students. Figure 3b displays the relationship between the share of college graduates in the cities top AMC scorers attended high school in and selective college attendance while controlling for student AMC rank, gender, race, high school cohort, test fixed effects (e.g. observation based on 2012 AMC 10 A), and grade fixed effects (e.g. observation taken while student was in 11th grade). The strong positive association suggests that exceptional math students from areas with low shares of college graduates are much less likely to attend selective universities when compared to students from areas with high shares of college graduates.

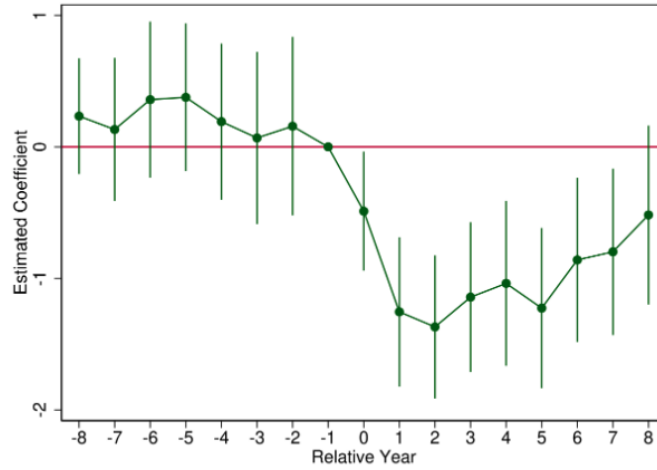
Figure 4: Mentor Effect on Revealing Talent Event Study (Negative Binomial)



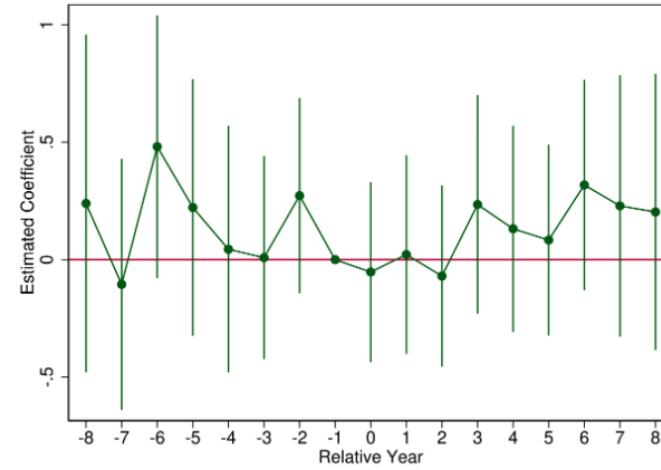
These figures display the negative binomial estimated event study coefficients from Equation 4 that capture the mentor effect on revealed math talent at schools (number of top AMC scores) in log odds with 95% confidence intervals provided. The relative year coefficients are centered on the first year a school had a Math League mentor. The flat pre-trends support the parallel trends assumption and the sharp increase suggests the impact of the mentors are quickly realized. Standard errors are clustered at the school level.

Figure 5: Mentor Effect on Revealing Talent Event Study (Zero-Inflated, Negative Binomial)

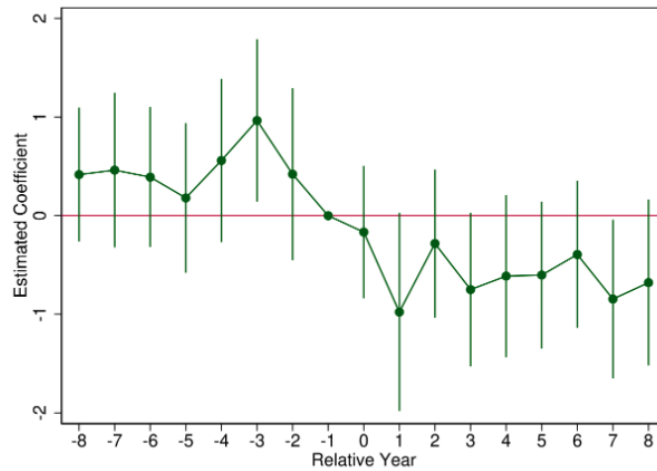
(a) Middle School (Inflate)



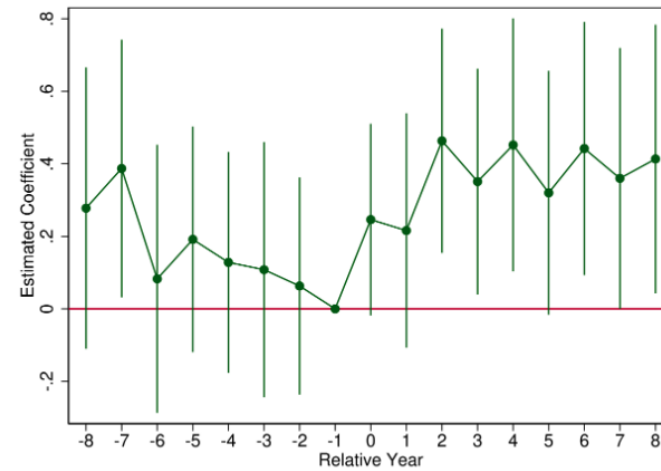
(b) Middle School (Count)



(c) High School (Inflate)

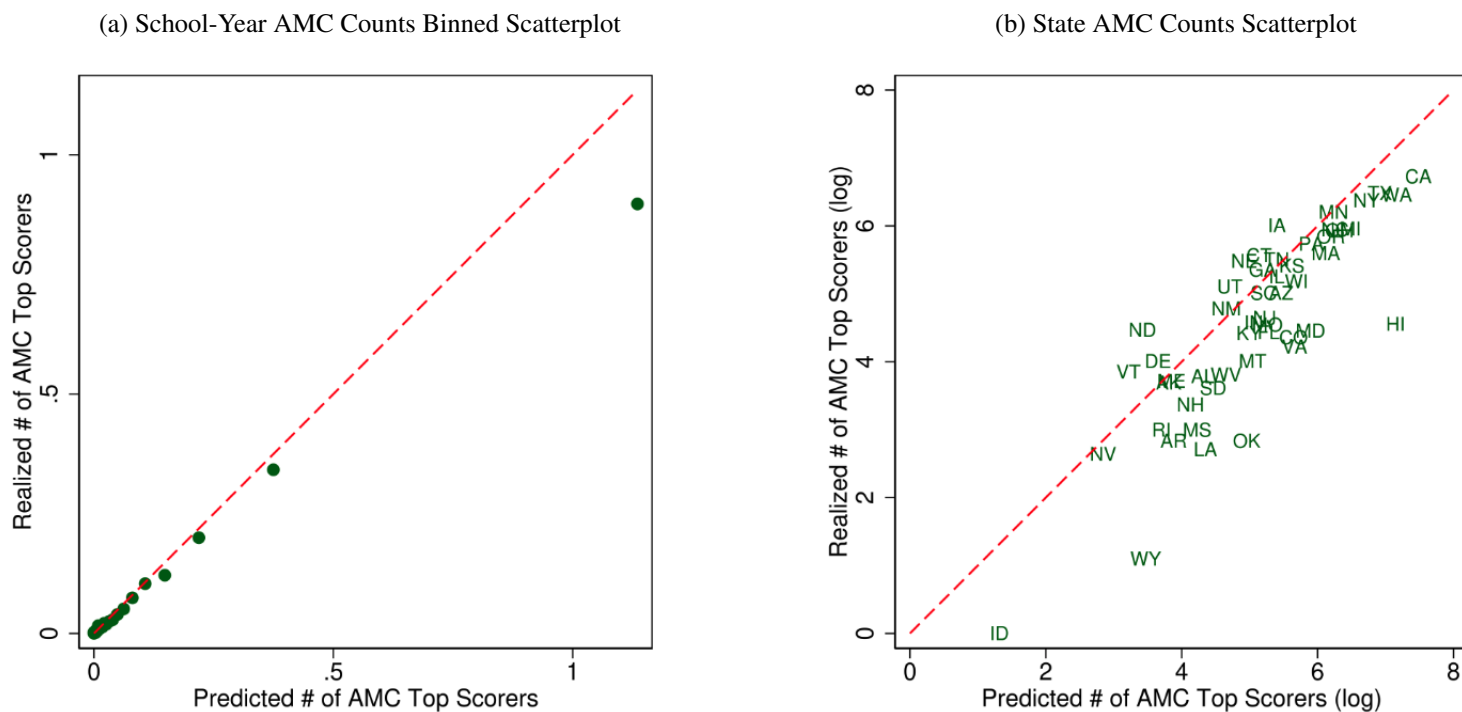


(d) High School (Count)



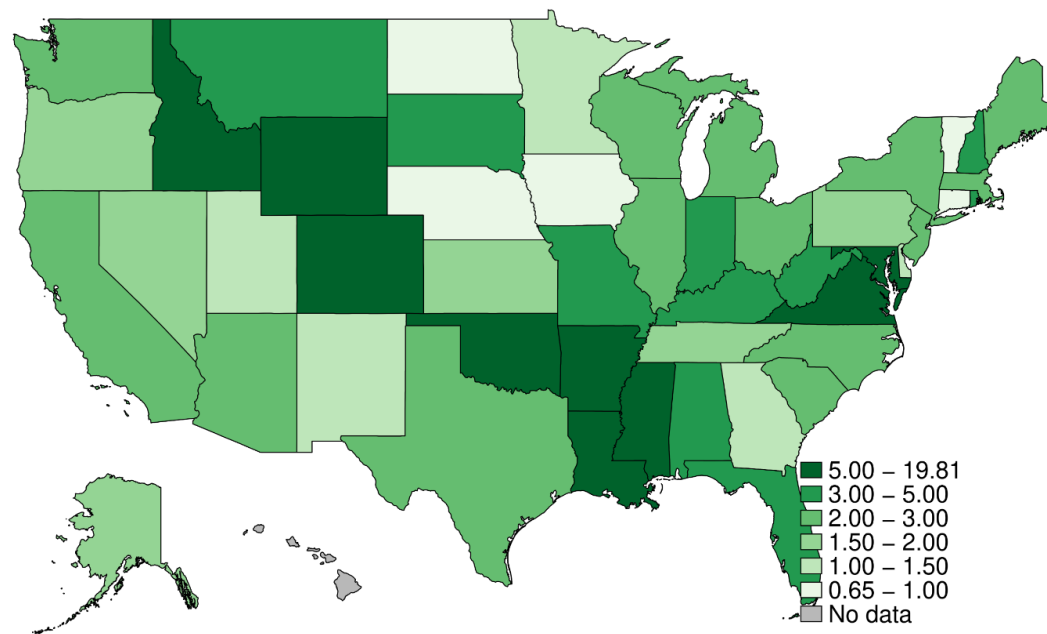
These figures display the zero-inflated, negative binomial estimated event study coefficients from Equation 4 with 95% confidence intervals. The relative year coefficients are centered on the first year a school had a Math League mentor. Standard errors are clustered at the school level.

Figure 6: Realized vs Predicted Top AMC Counts (Model Validation)



This figure demonstrates that the zero-inflated negative binomial estimated using the high school entry Math League sample demonstrates external validity when applied to the high school never Math League sample. Figure 6a is a binned scatter plot with twenty bins constructed using the sample of public, non-magnet, non-charter high schools that never participated in Math League (Table 5). 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 using the high school entry Math League sample and documented in Table 6. Figure 6b is a scatterplot constructed also using the sample of non-magnet, non-charter public schools that never participated in Math League (Table 5). 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 6. Together, these figures demonstrate that the zero-inflated negative binomial model estimated using the high school entry Math League sample does a good job of predicting revealed talent at out-of-sample schools, specifically, schools that did not have Math League mentor at any point from 1994 and 2020.

Figure 7: Missing Talent and Revealed Talent Ratio in the US



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 6 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 :

$$a_{ijk} = \beta_k X_i + \mu_{jk}^{stud} + \epsilon_{ijk}. \quad (10)$$

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

$$a_{ijk}^* = (\beta_k X_i + \mu_{jk}^{stud}) \mathbb{I}_{ijk} + \epsilon_{ijk}. \quad (11)$$

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:

$$A_{sjk}^* = \sum_{i \in N} a_{ijk}^* = \sum_{i \in M_{jk}} (\beta_k X_i + \mu_{jk}^{stud}) \mathbb{I}_{ijk} + \epsilon_{sjk}. \quad (12)$$

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

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

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 $|M_{jk}|$. 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:

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

where Z_s 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 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 school value-added can be written as:

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

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 suggest 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 credible signals of 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 Descriptive Evidence on Math Talent: Methods & Further Evidence

B.1 Tables

Table B.1: Summary of AMC-LinkedIn Matched Samples

(a) Summary Statistics for Top AMC Students (Middle School)

	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
MS AMC Rank	3,117.80	2,294.71	.	.
Top HS AMC	0.17	0.37	.	.
Selective University	0.22	0.41	0.02	0.14
Math	0.09	0.29	0.02	0.12
STEM Major	0.48	0.50	0.21	0.41
Earned PhD	0.08	0.27	0.02	0.13
Research Career	0.08	0.28	0.02	0.14
Observations	14,249		14,249	

(b) Majors of Top AMC Students (Middle School)

	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		

These tables provide summary statistics for the middle school AMC-LinkedIn matched samples. In Table B.1a, I compare top AMC students to a random reference sample of LinkedIn users. To construct the reference sample, I matched every top AMC student in the middle school AMC-LinkedIn matched sample to another college graduate of the same gender who graduated in the same year. Comparing the two samples highlights important differences between top AMC scorers and the average college graduate found on LinkedIn. In Table B.1b, I examine the majors pursued by top AMC scorers. The first column of this table displays the share of the students in the middle school AMC-LinkedIn matched sample who major in a given subject (double majors counted twice). The second column provides the rate that the students within a given major pursue a PhD. The final column lists the average AMC rank of students in the sample with a given major; the majors are sorted by these AMC rank averages.

Table B.2: Careers of Top Middle School AMC Students

(a) Job Titles				(b) Employers			
Job Title Word	AMC Sample	Ref. Sample	Ratio	Job Location	AMC Sample	Ref. Sample	Ratio
cofounder	65	1	65	amazon	32	0	.
cs	84	6	14	microsoft	28	0	.
phd	164	20	8.2	apple	22	0	.
md	45	6	7.5	capital one	18	0	.
scientist	184	33	5.6	epic	15	0	.
resident	112	20	5.6	university of california berkeley	15	0	.
sr	90	17	5.3	university of texas at austin	14	0	.
fellow	78	15	5.2	harvard university	11	0	.
professor	149	31	4.8	mit	11	0	.
software	721	168	4.3	mckinsey & company	11	0	.
researcher	86	20	4.3	purdue university	11	0	.
strategy	94	23	4.1	northwestern university	10	0	.
counsel	45	11	4.1	google	74	3	24.7
learning	58	16	3.6	meta	17	1	17
physician	102	29	3.5	university of washington	15	1	15
medicine	70	20	3.5	lockheed martin	15	1	15
candidate	180	53	3.4	facebook	13	1	13
research	225	69	3.3	university of michigan	13	1	13
computer	114	35	3.3	university of pennsylvania	12	1	12
mba	60	18	3.3	uc berkeley	12	1	12
science	199	64	3.1	duke university	10	1	10
engineer	1324	448	3	yale university	10	1	10
analytics	80	27	3	stanford university	26	3	8.7
writer	54	18	3	massachusetts institute of technology	13	2	6.5
attorney	112	39	2.9	georgia institute of technology	17	3	5.7

These tables provide insight on the careers of students in the middle school AMC-LinkedIn matched sample. Table 2a provides information on words appearing in the job titles of these students. The second column in this table reports the number of AMC students out of 10,000 students whose primary job title on LinkedIn includes the listed word. The third column shows the same frequency for the reference sample. The listed words are those that show up in the profiles of at least 0.5% of the AMC sample and have the highest frequency ratios. Table 2b provides information on employers of the AMC students. The second column in this table reports the number of AMC students out of 10,000 students who put the listed employer as their primary employer on their LinkedIn profile. The third column shows the same frequency for the reference sample. The listed employers are those that show up in the profiles of at least 0.1% of the AMC sample and have the highest frequency ratios. Both tables are sorted by the ratio between the AMC sample and reference sample frequencies. Together, these tables demonstrate top AMC students pursue highly quantitative careers in a variety of different fields and industries.

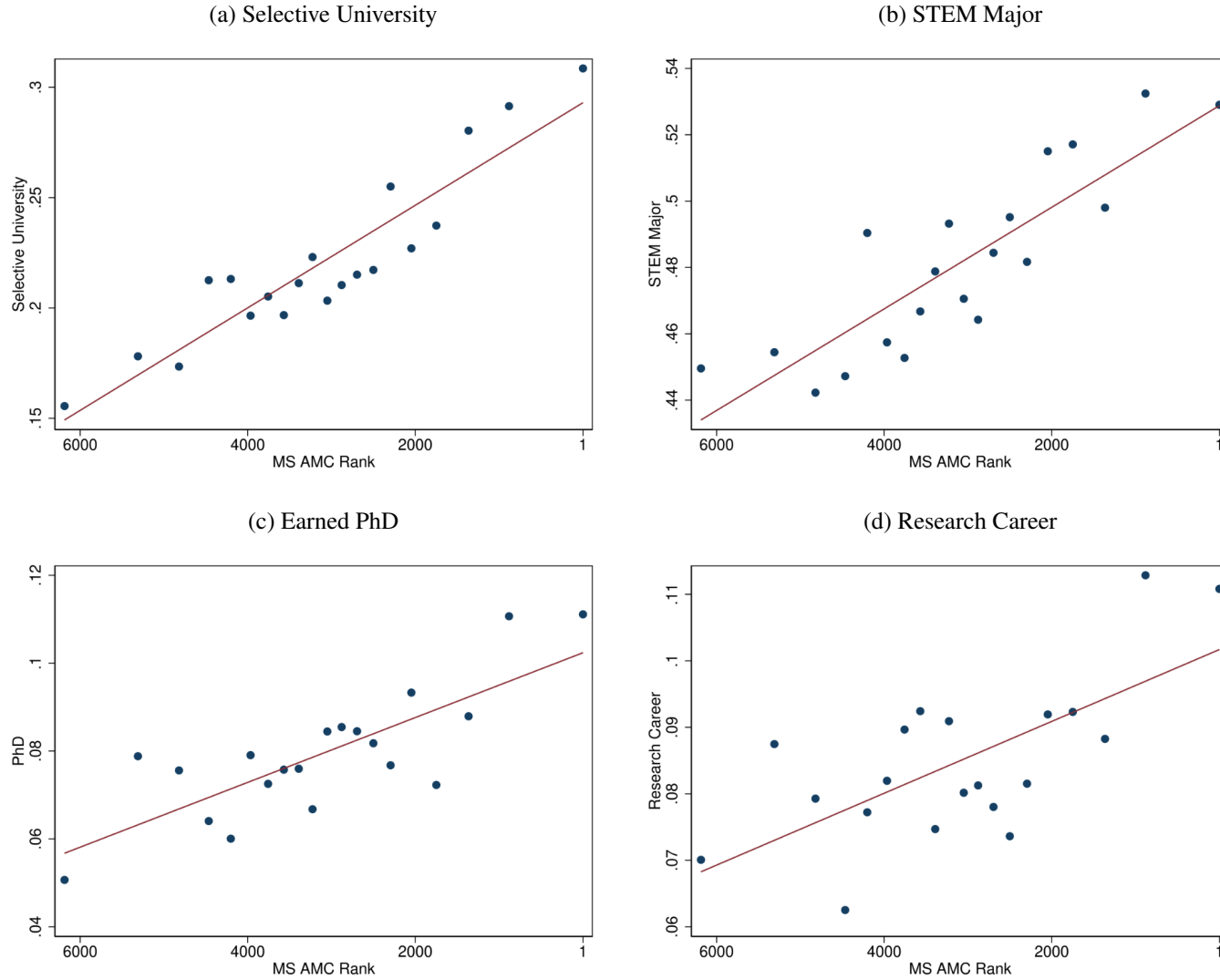
Table B.3: Descriptive Regression Estimation

	Top HS AMC	Selective BA/BS	STEM Major	PhD	Research Career
MS AMC Rank	0.0610*** (0.00222)	0.0232*** (0.00225)	0.0153*** (0.00255)	0.00737*** (0.00144)	0.00540*** (0.00163)
Female	-0.0392*** (0.00659)	-0.0405*** (0.00771)	-0.190*** (0.00904)	-0.00886* (0.00492)	-0.00378 (0.00490)
Asian/PI	0.0602*** (0.0112)	0.0455*** (0.0122)	0.0349** (0.0144)	-0.0106 (0.00652)	0.00331 (0.00767)
Other Race	0.00367 (0.0113)	0.0317** (0.0136)	-0.00925 (0.0147)	-0.0135 (0.00836)	0.00549 (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

This table reports the OLS estimated coefficients for Equation 2 for a selection of outcomes. These coefficients are estimated using the middle school AMC-Linkedin matched sample. The positive coefficients on AMC rank demonstrate that even among these exceptional math students, those who demonstrate greater mathematical ability on the AMC are more likely to have these later-in-life outcomes. The other coefficients demonstrate that gender and racial gaps in these outcomes persist even after controlling for ability—as demonstrated by AMC—and middle school. Standard errors are clustered at the school level.

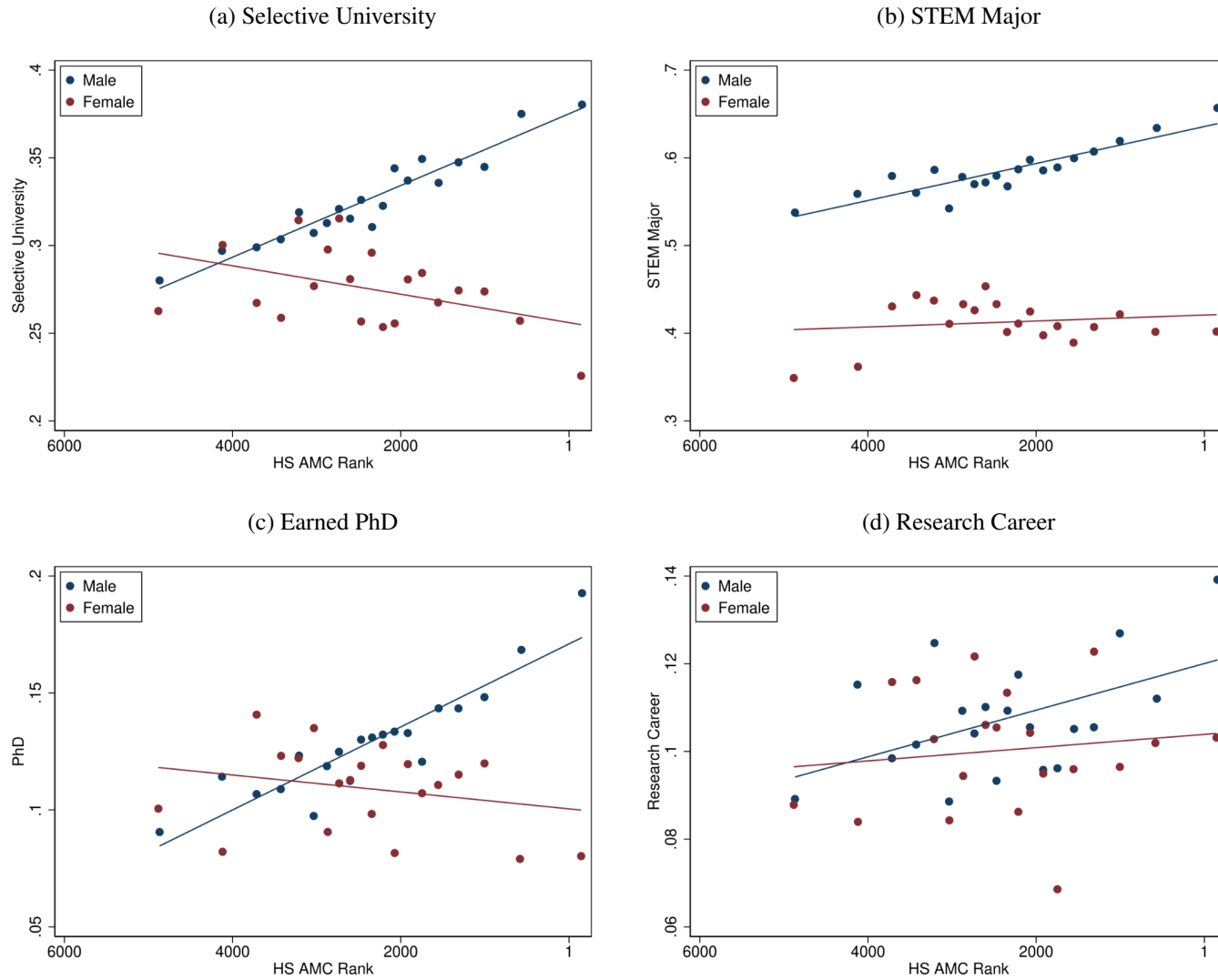
B.2 Figures

Figure B.1: Middle School AMC Rank vs Later-in-Life Outcomes



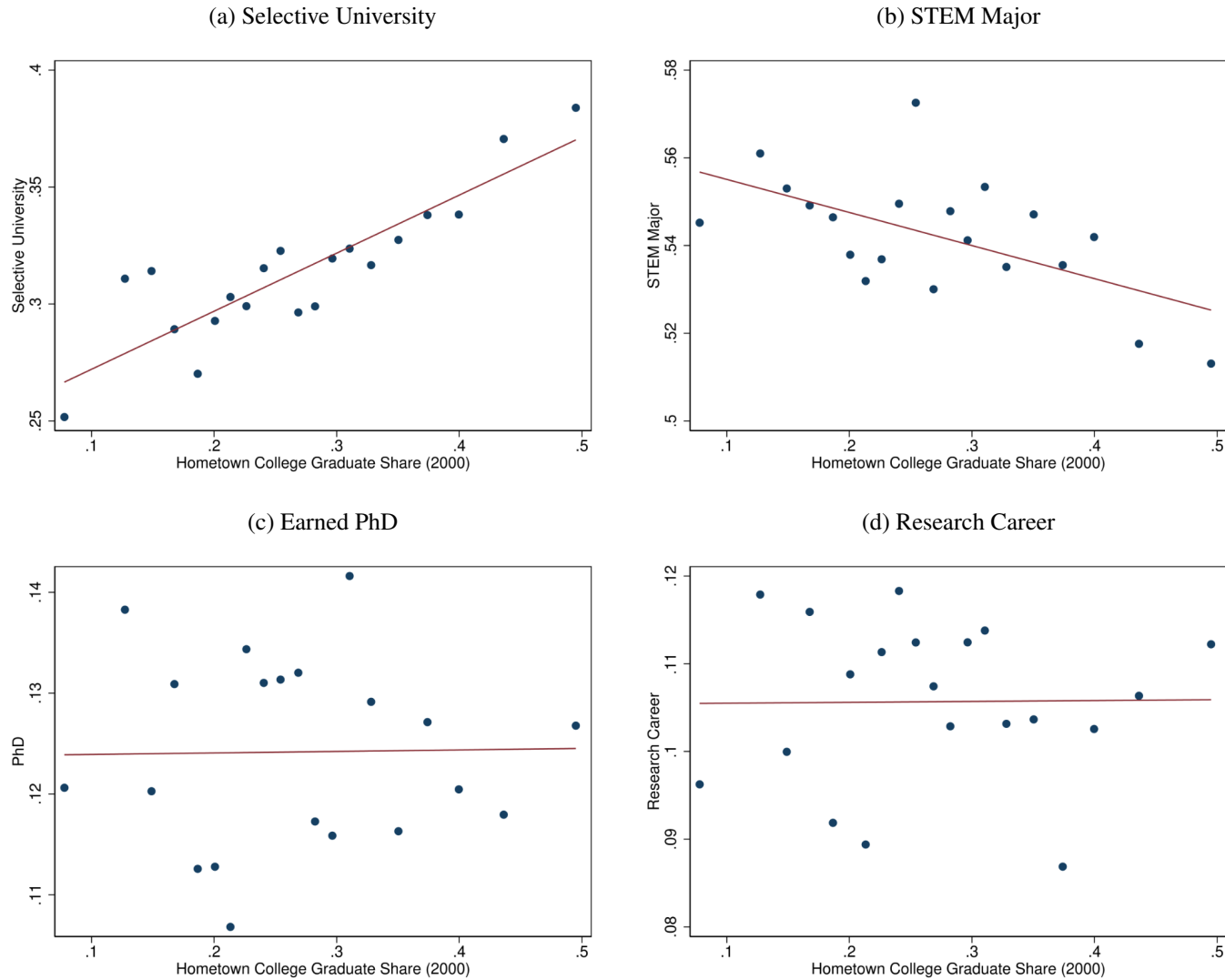
This figure displays a series of binned scatter plots between AMC 8 rank and later-in-life outcomes for students in the middle school AMC-LinkedIn matched sample. These plots are constructed while controlling for student gender, race, high school cohort, middle school fixed effects, test fixed effects (e.g. observation based on 2012 AMC 8), and grade fixed effects (e.g. observation taken while student was in 7th grade). These plots demonstrate there is a strong, positive relationship between middle school AMC rank and later-in-life outcomes associated with knowledge production even after controlling for demographic and socioeconomic conditions.

Figure B.2: High School AMC Rank vs Later-in-Life Outcomes by Gender



This figure displays a series of binned scatterplots between students' AMC 10/12 rank and various later-in-life outcomes by gender while controlling for student race, high school cohort, high school fixed effects, test fixed effects (e.g. observation based on 2012 AMC 10 A), and grade fixed effects (e.g. observation taken while student was in 11th grade).

Figure B.3: Hometown College Grad Share vs Later-in-Life Outcomes



This figure displays a series of binned scatterplots between the share of college graduates in the cities top AMC scorers attended high school in and selective college attendance while controlling for student AMC rank, gender, race, high school cohort, test fixed effects (e.g. observation based on 2012 AMC 10 A), and grade fixed effects (e.g. observation taken while student was in 11th grade).

C Heterogeneity in and Robustness of Difference-in-Differences Estimates

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

C.1 Tables

Table C.1: Heterogeneous Mentor Effect on Revealing Talent (Middle School)

	(1)	(2)	(3)
Mentor	0.464*** (0.110)	0.488*** (0.108)	0.808*** (0.0792)
Free Lunch Share	-2.119*** (0.318)	-0.875** (0.366)	-1.999*** (0.381)
Mentor \times Free Lunch Share	3.789*** (0.399)	2.748*** (0.448)	1.150*** (0.363)
City Pop. (log)	0.293*** (0.0257)	0.235*** (0.0269)	0.0687 (0.0457)
City BA Share	11.81*** (0.612)	6.236*** (0.613)	-2.911*** (0.998)
City Income (per capita)	-0.0385*** (0.00450)	-0.0141*** (0.00448)	0.0125* (0.00679)
School Enrollment (log)	1.105*** (0.0732)	0.560*** (0.0830)	0.766*** (0.131)
Asian Student Share	3.563*** (0.294)	3.315*** (0.269)	2.463*** (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

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

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 \times 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.

Table C.2: Heterogeneous Mentor Effect on Revealing Talent (High School)

	(1)	(2)	(3)
Mentor	0.348*** (0.0605)	0.342*** (0.0585)	0.245*** (0.0531)
Free Lunch Share	-1.962*** (0.258)	-1.024*** (0.275)	-0.622* (0.349)
Mentor \times Free Lunch Share	2.692*** (0.298)	1.805*** (0.304)	1.181*** (0.293)
City Pop. (log)	0.267*** (0.0156)	0.186*** (0.0156)	-0.0272 (0.0475)
City BA Share	11.21*** (0.384)	7.477*** (0.377)	5.214*** (1.114)
City Income (per capita)	-0.0531*** (0.00413)	-0.0348*** (0.00399)	-0.0384*** (0.0105)
School Enrollment (log)	1.329*** (0.0507)	0.838*** (0.0521)	0.951*** (0.105)
Asian Student Share	3.210*** (0.184)	3.030*** (0.174)	4.485*** (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

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

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.

Table C.3: Mentor Effect on Revealing Talent (OLS & Poisson)

	Middle Schools		High Schools	
	OLS	Poisson	OLS	Poisson
Mentor	0.215*** (0.0182)	0.720*** (0.0359)	0.108*** (0.0129)	0.346*** (0.0318)
Free Lunch Share	-0.0588 (0.0511)	-1.214*** (0.277)	0.0608 (0.0450)	-0.401 (0.271)
School Enrollment (log)	0.214*** (0.0326)	1.695*** (0.107)	0.0964*** (0.0303)	1.080*** (0.107)
Asian Student Share	11.57*** (0.219)	6.832*** (0.288)	6.520*** (0.217)	5.315*** (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

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

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.

Table C.4: Mentor Effect - Expanding AMC Access vs Improving Student Performance (ZIP)

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

Standard errors in parentheses

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

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.

Table C.5: Placebo Test using Never Math League Schools (Middle School)

	(1)	(2)	(3)
Mentor	0.0627 (0.0650)	-0.0600 (0.0690)	-0.0450 (0.0535)
City BA Share	13.71*** (0.426)	6.759*** (0.395)	-1.625** (0.643)
City Income (per capita)	-0.0458*** (0.00371)	-0.0274*** (0.00324)	-0.0229*** (0.00515)
Free Lunch Share	-1.918*** (0.155)	-1.272*** (0.194)	-1.697*** (0.217)
School Enrollment (log)	0.950*** (0.0368)	0.339*** (0.0436)	0.764*** (0.0737)
Asian Student Share	2.909*** (0.243)	2.825*** (0.229)	7.604*** (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

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

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.

Table C.6: Placebo Test using Never Math League Schools (High School)

	(1)	(2)	(3)
Mentor	-0.0809** (0.0401)	-0.0437 (0.0401)	-0.0183 (0.0395)
City BA Share	11.49*** (0.319)	6.250*** (0.296)	3.931*** (0.813)
City Income (per capita)	-0.0441*** (0.00338)	-0.0223*** (0.00302)	-0.0306*** (0.00724)
Free Lunch Share	-2.390*** (0.140)	-1.927*** (0.155)	-1.222*** (0.214)
log_students	1.252*** (0.0308)	0.395*** (0.0327)	0.881*** (0.0728)
Asian Student Share	1.948*** (0.175)	1.518*** (0.159)	1.651*** (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

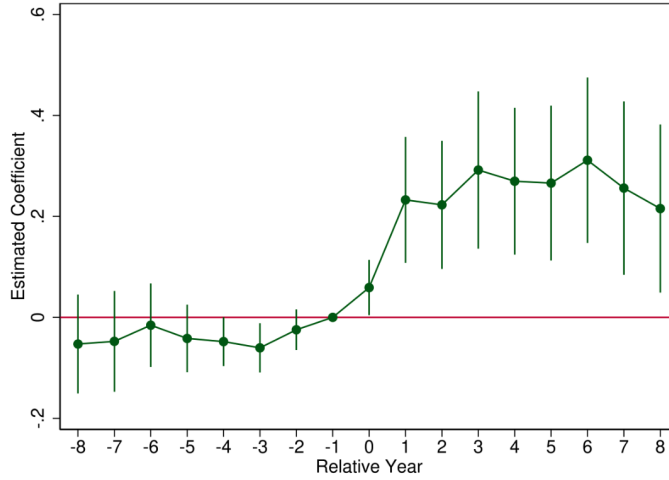
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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.

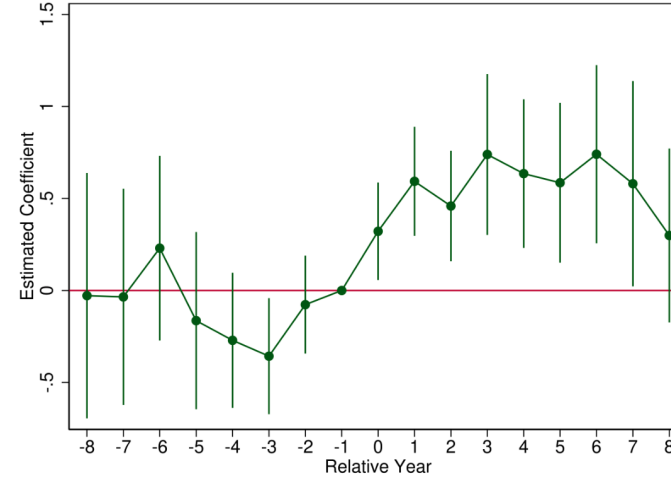
C.2 Figures

Figure C.1: Mentor Effect on Revealing Talent Event Studies (OLS, Poisson)

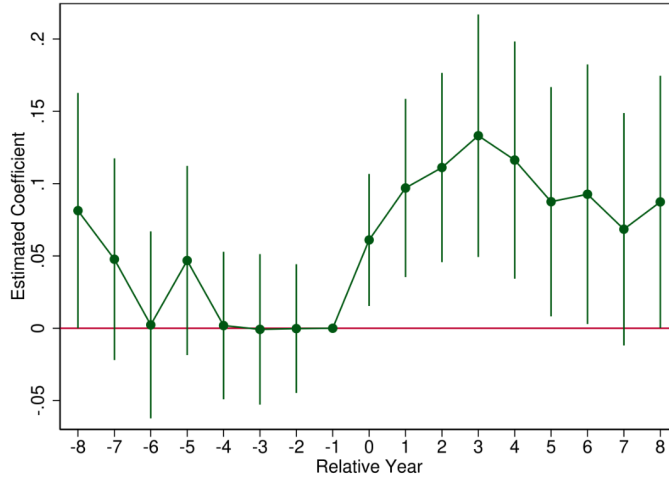
(a) OLS: Middle School



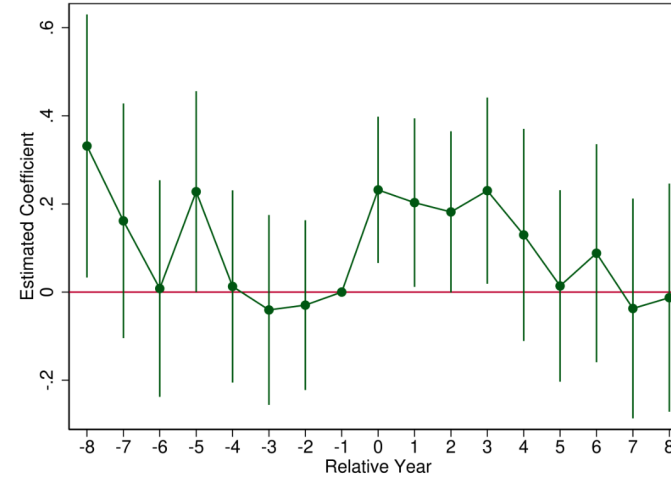
(b) Poisson: Middle School



(c) OLS: High School



(d) Poisson: High School



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.