Strength in Numbers: The Identification and Allocation of Exceptional Math Students

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1 Introduction

Exceptionally talented students have the potential to make unique contributions to society. They become productive researchers in a variety of STEM fields, inventors with highly cited patents, Fortune 500 executives, and even well-renowned tech founders (Committee on the American Mathematics Competitions , 1980–2023). By successfully identifying these students early in their lives, parents and educators can help them realize their full potential, which may have important consequences for the speed of scientific progress and economic growth. Given society benefits from scientific progress, research that connects the primary and secondary education of these students to long-run innovation and economic growth is especially important (Bloom et al., 2020).

There is evidence that many exceptional students fail to realize their full academic and scientific potential. Hoxby and Avery find most exceptional students from low income areas fail to apply to any selective college (Hoxby and Avery, 2014). Bell et al. find low-income students demonstrating exceptional math ability in 3rd grade are ten times less likely to patent later-in-life than their high income peers (Bell et al., 2019). These and related papers consistently point to information inequality and differential access to mentors as likely mechanisms for these low-high income achievement gaps. There are two key limitations to these papers: they rely on a measure of ability that is poor at the far right tail of the distribution and they are unable to identify likely mentors.

In my paper I explore how exceptional math students are identified and later allocated across colleges and professions in the US. This paper relies on novel data from national math competitions spanning more than four decades to measure the mathematical ability of exceptional math students and link them to likely mentors, their math coaches. I find that while the American Mathematics Competitions (AMC), a program dedicated to identifying math talent in children since 1950, is able to identify exceptional math students and distinguish talent at the fair right tail of ability, its popularity among schools has been steadily declining for decades, a trend that is consistent across multiple math competitions. This is despite participation being fairly cheap ($114 covers 30 students). This means the AMC is identifying exceptional talent at a much smaller set of schools than it did previously. Consequently, many exceptional math students are not found by the AMC.

Standardized tests like the ACT/SAT are imperfect substitutes for identifying exceptional math talent. These tests are designed for the general population and severely censer math ability. For example, Ellison and Swanson argue a score of 100 (out of 150) on the AMC 12 in 2007 is roughly equivalent to an 800 on the math section of the SAT (Ellison and Swanson, 2010, 2016). Over 3,000 students scored above 100 on the AMC 12 in 2007, meaning the ability of many of these students would be censored by the SAT, and that 3,000 figure only includes students at schools that offer the AMC. Importantly, this may have implications on how spots at highly-selective universities are allocated; these universities cannot distinguish the John Nashes from other exceptional students. Additionally, the ACT/SAT target juniors and seniors as they prepare to apply for college. The

AMC offers competitions designed to identify math talent as early as 7th grade, so exceptionally talented students may be identified earlier in their educations. Earlier identification may lead to parents, teachers, and/or the students themselves investing more in their own education prior to college. Indeed, stakeholders interested in advancing science and innovation by interventions targeting middle school and high school students, could use the AMC 8 to identify exceptionally talented math students across the US for their programs.

In one of my empirical strategies, I show that when schools first hire or appoint a math coach to organize Math League, another nationwide math competition, the school has significantly more top scoring AMC students. This causal effect appears trivial at first; these Math League coaches in many cases start the AMC program at their school as well and some of the students perform well. However, it implies there were exceptional students at these schools prior to the school joining Math League who did not have exposure to a math coach–who could serve as a mentor–and were not identified by the AMC. It also demonstrates that math coaches can help reveal talent in a decentralized fashion.

In another analysis, I provide evidence that continued exposure to math competitions in high school increases the probability students making the AMC Honor Roll in middle school major in STEM (1%) and attend an elite college (10%). There are a few possible mechanisms here. One is that the math coaches serve as mentors for these students. The coaches may help improve their students' abilities, provide guidance on the college application process, and write strong letters of reference with superior information about the student math ability. Another possible mechanism this exposure provides them with the opportunity to signal their math ability is beyond what can be measured by the ACT/SAT to colleges. Regardless of the exact mechanism, the results indicate the later-in-life decisions and outcomes of even the best math students can be influenced by external factors. This suggests there may be interventions which could nudge more these students to pursue STEM or be accepted/attend an highly-resourced undergraduate institution.

It would be difficult to overstate the influence of exceptional math students on innovation and economic growth. To study the allocation of these students across colleges, majors, and careers, I match high school AMC Honor Roll students to their online professional profiles using data from Revelio Labs. I consider this complementary to a similar analysis done by Agarwal and Gaule, which relies on International Math Olympiad students (Agarwal and Gaule, 2020). Their sample is composed of students from a wide variety of countries, but restricted to the six top students in each country each year. My sample is composed of only US students, but entails a broader ranger of exceptional ability, more than 3,000 students in most years. This broader range appears to lead to more diversity in subjects studied and careers pursued of the students.

For my sample of 26,664 matched students, I find 31% attend an elite college, 54% majored in STEM, 13% earn doctoral degrees, and 25% pursue careers as scientists or academics. The fields of science they pursue vary greatly; only 14% of the students major in mathematics, statistics, or

actuarial science. These rates are much higher than a comparable sample of college graduates with online professional profiles.

The probability of each of these outcomes increases with the math ability of these exceptional math students even after controlling for factors like school fixed effects. An improvement of AMC rank by 1,000 is associated with 9.1% higher probability of attending an elite undergraduate institution, a 7% higher probability of majoring in STEM, a 12.7% higher probability of earning a PhD, and a 6.3% higher probability of becoming a scientist or professor. This suggests students sort, or are sorted, by their math ability. This is true even beyond the performance level associated with a perfect SAT score, again suggesting the SAT is an imperfect substitute for stakeholders interested in identifying future scientists and innovators.

2 Mentor Productivity: School and Student Value-Added

In this section I provide a conceptual framework that outlines the impact of an activity-specific, school-level mentor. 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 measures and a student value-added measure, which may differ substantially for a given mentor. I then discuss how I will apply this framework to math competition coaches and exceptionally talented math students.

My model is closely related to teacher and school value-added models, but will differ in critical ways. First, while a teacher and school value-added models assume a student has a teacher and attends a school, 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, they are not forced to participate, but rather select into participation themselves, are encouraged by their parents, or are recruited by a mentor. Third, the mentor is exogenous; there is only one mentor for the activity at the school and, consequently, the student cannot select the mentor at their school.

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

$$a_{ij} = \beta X_i + \mu_j^{stud}. \tag{1}$$

This student achievement is realized if and only if the student participates in the activity, which may vary depending on the mentor. The indicator $\mathbb{I}_{ij}$ captures whether student i participates given mentor j's presence. The achievement realized by student i conditional on mentor j's presence is given by the product of a_{ij} and this participation indicator

$$a_{ij}^{*} = \left(\beta X_i + \mu_j^{stud}\right) \mathbb{I}_{ij}. \tag{2}$$

Let $M_j \subset N$ be the set of students for who participate in the activity given mentor j's presence. I define the activity-specific, school achievement to be the sum of the achievements of those participating in the activity:

$$A_{sj}^{*} = \sum_{i \in N} a_{ij}^{*} = \sum_{i \in M_j} \left(\beta X_i + \mu_j^{stud}\right). \tag{3}$$

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

$$A_{sj}^{*} = |M_j| \left(\beta \bar{X}_j + \mu_j^{stud}\right), \tag{4}$$

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

Let $j = 0$ correspond to the absence of a mentor. In the case of no mentor, $a_{i0}^{*} = 0$ and, consequently, $A_{s0}^{*} = 0$. 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 coach. While teacher value-added models almost always consider relative quality because a student must have 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 latent student achievement within a domain 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:

$$A_{sj}^{*} = \gamma Z_s + \mu_j^{schl}, \tag{5}$$

where Z_{st} are school characteristics and μ_j^{schl} is the school-level mentor effect. This serves as the

school analog to Equation 2, and I refer to μ_j^{schl} as mentor j's school value-added. Considering counterfactuals over mentor quality is easier here; a mentor with with higher μ_j^{schl} leads to greater school achievement regardless of the school. By combining equations 4 and 5, the relationship between school value-added and and school value-added can be written as:

$$\mu_j^{schl} = \left|M_j\right| \left(\beta \bar{X}_j + \mu_j^{stud}\right) - \gamma Z_{st}. \tag{6}$$

The difference between μ_{ij}^{stud} and μ_j^{schl} here is subtle. While μ_{ij}^{stud} depends only on the mentor's ability to impact student achievement, μ_j^{schl} depends on this ability as well as the mentor's ability to recruit students (M) and the type of students they recruit $\bar{X}_i$. 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 student's ability to play in 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.

In this paper, I apply this framework to math competition coaches. I am primarily interested whether or not the math coaches can help reveal exceptionally math talent at schools, A_{sj}^*. I then examine whether or not being identified as exceptionally talented influences the choices or later-in-life outcomes of the identified students.

3 Data

My research question has high data requirements. I need a large, geographically and temporally diverse sample of high ability students, information on their high schools, and the ability to observe their later-in-life choices and outcomes. Consequently, I makes use of a variety of data sources. I provide a brief overview of the four most important sources in this section: the American Mathematics Competitions (AMC), Math League, the U.S. Presidential Scholars Program, and Revelio Labs LinkedIn data.

3.1 American Mathematics Competitions (AMC) Data

I constructed a novel dataset of exceptionally talented math students by compiling results from the American Mathematics Competitions (AMC) from 1980 to 2022. The results from 2011 to 2022 were compiled using the AMC digital archive. The results from 1980 to 2010 were gathered from physical books covering national results, which were sent to participating schools each year. The AMC no longer held these books, so I contacted thousands of current and former math teachers across the United States in order to locate copies. A handful of these teachers held onto these books from when they organized the AMC at their school and generously donated them. I then digitized these books and used Optical Character Recognition (OCR) to extract necessary data.

The results cover a variety of competitions including the AMC 8, AMC 10 A/B, AMC 12 A/B, the American Invitational Mathematics Examination, and the United States of America Mathematical Olympiad. For each of the competitions, the results provide general summary statistics as well as lists of high scoring students. The summary statistics include information on the number of schools and students participating in each competition, the score distribution for the competitions, and competition commentary from the AMC leadership. The student lists report information on each student exceeding a score threshold, which may vary by year and grade. This information includes the student's score, first initial, last name, grade, school, city, and state. In total, the high school observations exceed 500,000 while the middle school observations exceed 300,000.

This paper primarily uses the data from AMC 8 and the AMC 12 A/B student honoree lists. The AMC 8 and AMC 12 A/B are the organization's flagship middle school and high school competitions, respectively. In Figure 2, I show the number of students who make the AMC 8 honoree list and the number of students who make the AMC 12 A/B honoree list over time. The sudden shifts in the number of honorees, especially for the AMC 12 A/B, result from shifting AMC policies and "random" shocks in the difficulty of competition questions.

For every student listed, I determine their score rank, the measure I use to compare students across years. 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 decreasing dramatically over the sample period. Score rank suffers from the same problem as the score percentile, but to a lesser extant; 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. I note that in most years, being rank 3,200 is sufficient to make the AMC 8 and AMC 12 Honor Rolls. I leverage this threshold for a school level outcome during a later in analysis.

A limitation of the AMC results is that they do not report the complete list of participating schools. While I can generate a partial list from the student honoree lists, most schools fail to have any students make these lists for a competition. Consequently, I cannot tell if a school had zero AMC high scorers because they did not compete or they had zero AMC high scorers because they competed, but did not have an exceptional math student. This limits the ability of the raw data to speak to the true distribution of exceptional math talent in the US.

3.2 Math League Data

I obtained administrative data from Math League, Inc. for the entire US from 1994 to 2020. This administrative data includes account, contact, and order records for all the schools that participated in Math League during this period. Each school has an account in the account records where school names and detailed location information can be found. For each of these accounts, the contact records provide the set of names and email addresses of the staff and faculty members who have placed orders with Math League. The order records list the transactions made by accounts with the

associated contact included. These order records include annual competition registrations as well as competition prep book orders.

The Math League administrative data allow me to determine the set of schools participating in each competition over time. This is in contrast to the AMC data, where I cannot accurately predict participation. Perfectly knowing when these competitions are offered is crucial for my later empirical strategies where I estimate the impact these competitions and math coaches have on the revealed talent at schools. Thus, this feature of the data is necessary.

I have also obtained the school result reports for the elementary, middle, and high school Math League competitions for most of this period. These reports contain information on each school's performance as well as lists of students who received a perfect score. These student lists provide full student name until 2007 after which they list student first name and last initial. While I do not use the school performance data in this paper, I do use the student lists to aid in matching AMC students to their online profiles.

3.3 National Center for Education Statistics Data

I collected data on public and private primary and second secondary 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, which provides biennial records for most[1] private schools extending back to 1989.

The CCD and PSS data provide information on school names, geographic locations, grades offered, student enrollment and demographic counts, and faculty employment. For private school data in odd number years, I simply use PSS data from the previous even number year. Based on the school identifying codes, the CCD data from 1986 to 2020 include 160,760 unique public schools, of which 43,904 offer 12th grade. On the private school side, the PSS data from 1989 to 2020 include 80,497 private schools with 21,766 ever offering 12th grade.

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

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

3.4 Revelio Labs

I use data from Revelio Labs covering the online professional profiles of 700+ million to determine the later-in-life outcomes of the students in the AMC sample. These profiles provide full names of users and information on their current and previously held jobs, their educational history, and demographic information like gender and race. In many cases, the educational history provides graduation data which allows me to obtain an approximate measure of age.

I match the AMC students to these profiles through an elaborate process. As a brief overview, I match exactly on first initial, last name, and either high school or college graduate year; perform a fuzzy matching using the high school listed on LinkedIn when available; and build a logit model to calculate the probability a potential match leads to an exact first name match using a training sample of AMC students for whom I know their full first name. After applying the logit sample to the broader set of data, I restrict my sample to matches with a sufficiently high predicted probability of resulting in the correct first name. This process is described in much more detail in Appendix 1.

4 Math Coaches and the Identification of Talent

I test whether the presence of a Math League coach influences the amount of observable math talent at a school. I leverage the arrival of the first Math League coach at a school to estimate the causal effect of a school having a Math League coach on the probability a school participates in the AMC and on the number of exceptional math students identified at the school. Leveraging these entry events for a difference-in-differences design, I find the presence of a Math League coach increases the probability a high school participates in the AMC by 67% and increases the number of exceptional math students identified by the AMC at the school by 61%. A series of robustness checks support the identification of these estimates.

PARAGRAPH ON EXPOSURE RESULT

4.1 Math Coaches: Revealing Talent

In this section I estimate the impact a math coach has on identifying and foster exceptional math talent at a school. To establish causality, I use a difference-in-difference design on the introduction of Math League to the set of non-magnet, public schools that had not offered Math League prior to 1994. The estimates indicate these math coaches increase the probability a school participates in the AMC (53%) and increases the number of top AMC scorers found at school already participating in the AMC (64%). A variety of robustness tests help validate these results.

In the ideal experiment, I would have a large set of non-magnet, public schools and randomly allocate Math League coaches across these schools. I observe AMC participation prior to this randomization as well as the number of top AMC scorers found at each school during each year. I

could then directly estimate the impact of math coaches on the probability a school participates in the AMC and the number of top AMC scorers found at a school by regressing these outcomes on an indicator for whether the school had a math coach:

$$AMC_participation_{st} = \alpha + \beta math_coach_{st} + \varepsilon_{st}, \tag{7}$$

$$AMC_scorers_{st} = \alpha + \beta math_coach_{st} + \varepsilon_{st}. \tag{8}$$

Reality differs notably from this ideal. First, math coaches are not randomly allocated across schools. Schools in communities with higher incomes or higher shares of college graduates are much more likely to have a math coach. Second, I cannot observe AMC participation in a given year; I can only observe the number of top AMC scorers at a school. With sufficient controls, X_{st}, I could theoretically handle this first problem and disentangle the influence of community and other school characteristics on these outcomes from the impact of a math coach. The regression in this case would only differ from the ideal experiment in that it would incorporate the rich controls. The second problem, the inability to observe AMC participation, is more complex.

If I were able to perfectly observe AMC participation, I could estimate the impact of a math coach on participation and their impact on the number of top scorers separately. However, I do not observe participation, but only the number of top AMC scorers at schools. Consequently, the zero counts correspond to two separate scenarios. In the first scenario, the school does not participate in the AMC, so the school necessarily has zero top scorers. This is called a *structural zero*. In the second scenario, the school does participate in the AMC, but no student performs well enough to become a top student. This is called a *random zero*. These two zeros are drawn from two separate distributions and suggests I may need to estimate my model as zero-inflated estimation method.

For estimation, I rely on a sample of marginal schools; schools that join Math League for the first time between 1994 and 2020. I begin by identifying all 12th grade offering non-charter, public and private schools present in the NCES data every year from 1994 to 2020. I then restrict the sample to schools which join Math League for the first time between 1994 and 2020. This restriction is important for my identification strategy and limits the analysis to schools that are on the margin of participating in Math League, which I can observe before and after joining Math League. Schools in my sample first join Math League during different years throughout the sample period, though they become less common later in the sample, especially after 2010 (Figure 3). Many of these schools participate in the AMC and have top AMC students prior to joining Math League (Figure 4).

In Table 1, I compare the set of schools in my sample to the high schools present in the NCES data every year from 1994 to 2020 that never offered Math League during those years.

To identify math coach effects, I use a generalized difference-in-differences strategy. I regress the number of top AMC scorers on an indicator for whether the school is participating in Math

League, year fixed effects, school fixed effects, and time-varying school characteristics (number of enrolled students, teacher-student ratio, share of API students, share of white students, share of black students, share of hispanic students):

$$y_{st} = \alpha + \beta math_coach_{st} + \tau_t + \pi_s + X_{st}\lambda + \varepsilon_{st}. \tag{9}$$

I estimate this model using three separate estimation methods: ordinary least squares (OLS) regression, negative binomial (NB) regression, and zero-inflated negative binomial regression (ZINB).

Each of these approaches their own strengths and weaknesses. If identification holds, the estimated coefficient of interest, $\hat{\beta}$ will capture the causal impact of a math coach joining a school on the exceptional math talent discovered at the school via the AMC.

The estimated coefficients are provided in Table 2 and all indicate joining Math League increases the amount of top 3,200 AMC students found at a school. The OLS estimate, $\hat{\beta}^{OLS} = 0.128$, suggests the joining Math League increases the number of top AMC students by 0.128 students, which exceeds the mean by nearly 50%. The negative binomial estimate, $\hat{\beta}^{NB} = 0.402$, and the count portion of the zero-inflated negative binomial estimate, $\hat{\beta}^{ZC} = 0.476$, are given as log-odds. They are in close agreement and suggest joining Math League increases the number of top AMC students found at a school by between 48% and 60%. The inflate $\hat{\beta}^{ZI} = -0.837$ is also given in log odds and has a much different interpretation. It indicates that, conditional on having zero top 3,200 AMC scorers, the probability the zero is a structural zero (meaning the school did not participate in the AMC) is 43.3% lower if the school joined Math League.

Given the outcome of interest is a right-skewed count variable with two different types of zeros, the zero-inflated negative binomial strategy is the most appropriate. It has the additional advantage of separating the impact of a math coach on the count of top AMC scorers assuming participation from the impact from simply introducing the AMC at a school. The primary weakness of this strategy is that estimation fails to converge when school fixed effects are added, meaning there may be important unobservable school characteristics that are not controlled for. The other two strategies do control for school fixed effects and yield similar estimates, which provides reassurance that the results are not driven by such uncontrolled school characteristics.

My analyses suggest there are many exceptionally talented math students at schools that do not participate in the AMC, Math League, or have a dedicated math competition coach. The estimates from these difference-in-difference strategies indicate that expanding access to these activities and resources would reveal many more of these exceptionally talented math students than are currently being identified by the AMC.

Reflecting on the conceptual model in Section 2, there are a few different mechanisms which may be driving these effects. I will discuss these from the perspective of the arriving Math League coach. If a school did not offer the AMC prior to the Math League math coach starting the program, the math coach my simply be increasing access to the AMC. They increase A^*_{sjt} by providing an

activity students did not have before. If a school did offer the AMC prior to the math coach starting the program, the math coach may be better at *recruitment*, *selection*, and *improvement* than the previous AMC facilitator. In the case where the math coach was the previous facilitator, joining Math League may simply coincide with the math coach dedicating more resources and energy to the activity. While I cannot disentangle these mechanisms because I do not observe AMC participation itself, the causal effect is still important: increasing access to a math coach at a school helps identify exceptionally talented students.

4.1.1 Robustness

In this section I perform a series of robustness exercises to validate identification of the difference-in-difference estimates. In the first, I estimate the event study equivalent of my difference-in-differences strategy. This confirms there are no pre-trends in the number of top AMC scorers leading up to a school joining Math League. In the second exercise I implement a placebo regression during which I randomly mix up the treatment status and timing of schools. This ... . In the final exercise, I replicate the entire analysis using middle schools. The results are quite similar.

It is possible my difference-in-difference estimates are driven by unobserved shifts in the talent at schools. For example, over a series of years the student quality at the schools in my sample could be increasing, which causes schools to hire or appoint a math coach. If this were the case my estimates would be biased upwards as they would fail to account for the shifting talent. To test whether this is occurring, I recast my difference-in-differences specification as an event study. Instead of a dynamic indicator for whether a school has a Math League coach in a given year, the event study has indicators for whether the school year observations aligns with a given year relative the school first having a Math League coach, $I\left[t = k + T_s^{(entry)}\right]$, as well as an indicator for whether the school had previously had a Math League coach but no longer does, no_coach_{st}. Together the coefficients, $\beta^{(entry,k)}$, capture the trend in the number of top AMC scorers before and after a school first has a Math League coach, while controlling for whether the coach remains active in the post period.

$$y_{st} = \alpha + \sum_{k=-25}^{25} \beta^{(entry,k)} I\left[t = k + T_s^{(entry)}\right] + \beta_0 no_coach_{st} + \tau_t + \sigma_s + X_{st}\lambda + \varepsilon_{st} \tag{10}$$

As with the difference-in-differences strategies, I estimate these event studies using OLS, negative binomial, and zero-inflated negative binomial regression. Like before, the zero-inflated negative binomial estimation will not include school fixed effects.

For all three estimation methods, there are no pre-trends in the event studies and the estimated coefficients shift sharply during the year of the event. This is displayed graphically in Figure 5, where I show the estimated event study coefficients, $\beta^{(entry,k)}$, for $|k| \leq 8$. These support for identification in the difference-in-differences estimation by indicating there is no increase in the amount

of observable exceptional math talent leading up to the school first joining Math League. It remains possible that these schools first join Math League in the exact year the school receives a positive and persistent influx of exceptionally talented math students. Given data limitations this would be challenging to rule out, though it seems unlikely.

I show that there is no change in the amount of exceptionally talented all-around students coinciding with schools joining Math League. I do this by estimating the event study with the outcome being the count of Presidential Scholar Candidates found at a school. These counts have a similar over-dispersion issue as the top AMC scorer counts, but there are no structural zeros, so I use negative binomial regression for this estimation. I show the estimated event study coefficients, $\beta^{(entry,k)}$, for $|k| \leq 8$ for this outcome in Figure 6. The trend in the coefficients is flat with no shift in the pre-period and post-period, suggesting there is no change in the number of exceptionally talented students around the time the school first offers Math League.

A placebo test where I randomly assign the sequence of difference-in-difference variables, $math_coach_{st}$, from one school in my sample to another school in my sample, adds further credibility to my estimates. After the random assignment of the math coach indicators, I estimate the difference-in-difference coefficients as I did before. The resulting estimates, shown in Table 3, are much smaller than in the original estimation and are statistically insignificant. This reduces the possibility the original effects I estimated are actually the result of some uncontrolled, unobservable time trends.

4.2 Fostering & Placing Talent

In this section, I test whether exposure to high school math competitions impacts the later-in-life outcomes of students who have already demonstrated exceptional mathematical ability in middle school through the AMC 8. Unsurprisingly, exceptional math students exposed to high school math competitions are more likely to become top AMC 10 and AMC 12 performers. More importantly, this exposure appears to impact whether these students attend an elite college or pursue a STEM major.

The ideal experiment in this case would be to identify a sample of exceptional middle school math students and randomize their exposure to a high school math coach and high school math competitions. Randomization at the student-level would allow me to control for school effects, while randomization at the school-level concerns regarding spillovers. I could use the AMC 8 to identify students for such an experiment. However, providing students with math coaches would be quite costly and observing later outcomes of interest (e.g. college and major choice), would take at least four years.

I instead exploit student variation in proximity to a high school offering Math League. For every student in the AMC 8 Honor Roll, I determine whether there is at least one high school within three miles of their middle school which would offer Math League during the students high school years.

This serves as my measure of high school math coach and competition exposure and is captured by the indicator $ML_exposure_i$, which is equal to one if and only such a high school is available to student i. Ideally, I would know which high school each of these students actually attend, but this is impossible to determine in many cases, which leaves me with this strategy.

I restrict the sample of AMC 8 Honor Roll students to those I am able to accurately match to in the Revelio data. This matching process is fairly elaborate and is outlined in Appendix A. The Revelio data allow me to observe the colleges and majors attended by these students. I provide summary statistics for this matched sample in Table 4 by high school exposure. The pre-high school variables are very similar across the subsamples. While there are some racial differences with the exposed sample the samples are remarkably similar. The definition of the sample requires students to have attended a middle school that offers the AMC 8, which means these students are in relatively similar communities. Gaps exist, however, for the share of students becoming top 3,200 AMC scorers, the share attending an elite college, and the share majoring in STEM.

To estimate the impact a high school math coach has on these exceptional math students I regress various outcomes such as whether or not the student is near a high school which offers Math League $ML_exposure_i$, rich student, school, and community controls (X_{ist}), year fixed effects (τ_t), and location fixed effects (σ_s). The student controls include the student's AMC 8 rank, high school graduation cohort, race, and gender. The school controls are based on the middle school of the student during the year the are observed in the AMC 8 data and vary across time. These include the log sum of 6th, 7th, and 8th grade students, the student teacher ratio at the school, and student race ratios. To control for community characteristics per capita income and college graduate ratio of the middle school's city in the year 2000. I also switch between using state and county fixed effects to control for time invariant location characteristics:

$$y_i = \alpha + \beta_0 ML_exposure_i + \beta_1 amc8_rank_i + \tau_t + \sigma_s + X_{ist}\lambda + \varepsilon_{ist}. \tag{11}$$

I estimate these models using logistic regression; the estimated coefficients on $ML_exposure_i$ are provided in Table 5 and suggest students exposed to math competitions in high school are more likely to attend an elite college and major in STEM in addition to continuing their success on the AMC 10 and 12. The estimated coefficients on $amc8_rank_i$ indicate students who demonstrate better math ability are more likely to have these outcomes as well, consistent with expectation. This later pattern suggests there is sorting by math ability and is discussed more detail in Section 5. Here, these later coefficients primarily serve as a reference point.

5 The Allocation of Exceptional Math Talent

In this section, I provide a series of descriptive facts about the allocation of top AMC students across majors, colleges, and careers. These facts lead to three key takeaways: (1) top AMC students play

a highly disproportionate role in science, not just math, relative to the average college graduate, (2) among top AMC students, those who perform better in the competition play an even greater role in science, and (3) even among the best AMC students, there are sizeable demographic gaps in those that pursue science and attend resource rich colleges. Together, these takeaways suggest there is "missing scientific innovation" resulting from a misallocation of exceptional math talent. They also suggest the AMC could be used to identify exceptional students for incentives or interventions aimed at increasing the stock of high-quality scientists.

The descriptive evidence provided in this section relies on a sample of 26,664 AMC students whose LinkedIn profiles I match to using the Revelio Labs Data. This matching process is elaborate. I match exactly on first initial, last name, and either high school or college graduate year; perform a fuzzy matching using the high school listed on LinkedIn when available; and build a logit model to calculate the probability a potential match leads to an exact first name match. This process is described in much more detail in Appendix A. The patterns presented in this section are consistent with those found using a smaller, much more conservative sample relying on high school name matches. Appendix B provides a replication of the analyses in this section using this more conservative sample.

To allow for broader comparison, I build a reference sample of US college graduates on LinkedIn. For each of the 26,664 students in my matched AMC sample, I randomly select a US LinkedIn user who graduated from a US college in the same year as the AMC student. This sample provides a benchmark for the allocation of college graduates on LinkedIn while controlling for the temporal variation in the AMC sample.

5.1 Majors, Colleges, and Careers of Exceptional Math Students

AMC students major in STEM (54%), attend elite undergraduate institutions (31%), earn doctoral degrees (13%), and pursue research careers (25%) at very high rates (Table 6). Compared to the matched sample of college graduates on LinkedIn, they are more than 2.5 times likely to major in STEM, 15.5 times more likely to attend an elite undergraduate institution, 5.5 times more likely to earn a PhD, and 5 times more likely to pursue a research career. Demographically, these AMC students are majority white, but share of Asian/Pacific Islander students is three times that found in the reference sample.

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 14% of the sample major in mathematics, statistics, or actuarial sciences. Higher shares of these students major in engineering (21%), computer science (14%), and social science (14%). Other common majors include the life sciences (7%), physics/astronomy (5%), and chemistry/biochemistry. Many of the students in these majors continue and earn a PhD and work as

a professor or scientist (Table 7).

Many of these AMC students have a mathematical ability that is censored by traditional pre-college measures like the ACT/SAT. Ellison and Swanson argue that an AMC score of 100 on the 2007 AMC 12 A (Rank 2,812) is roughly equivalent to a perfect SAT math score and also serves as a more reliable measure of ability. Yet, relative AMC performances continue to have predictive power beyond this range of ability for the probability students major in STEM, attend an elite undergraduate institution, earn doctoral degrees, and pursue research careers, researcher, or professor (Figure 7). These relationships persist even after linearly controlling for student gender, race, high school graduation year fixed effects, and the share of college graduates in the student's high school town (Figure 8).

To estimate the association between these outcomes and AMC performance, I regress each outcome (y_i) on AMC rank (amc_rank_i) while including controls for student gender, race, grade during observed AMC test, AMC test, hometown share of college graduates (X_i), state fixed effects, and high school graduation cohort fixed effects (τ_t). I make amc_rank_i negative so a positive coefficient an increase in amc_rank_i corresponds to an improvement in AMC performance.

$$y_i = \alpha + \beta amc_rank_i + \gamma_t + \delta_s + X_i\lambda + \varepsilon_{ist} \tag{12}$$

The models (Equation 12) are estimated using logistic regression for the four outcomes. I use state fixed effects and hometown share of college graduates instead of high school fixed effects because many high schools only have one student in the AMC-LinkedIn matched sample, and school fixed effects would force those observations to be excluded from the regression. The estimated coefficients are provided in Table 8. The omitted coefficients are those associated with white, male students.

The estimates indicate a 1,000 rank improvement in AMC performance is associated with a 9.1% higher probability of attending an elite undergraduate institution, a 7% higher probability of majoring in STEM, a 12.7% higher probability of earning a PhD, and a 6.3% higher probability of pursuing a research career. The estimates are all highly statistically significant. Compared to the relationship between these outcomes and hometown college share, the AMC rank coefficients are sizeable.

These outcomes result from the decisions of individual students and educational institutions, so the relationships between these outcomes and AMC performance capture a combination of self-sorting and institutional screening. Controlling for background, better performing students may believe they have a higher comparative advantage in STEM and, consequently, seek out more prestigious universities, major in more quantitatively rigorous fields, and be willing to pursue PhDs and research careers. This is self-sorting. At the same time, undergraduate and graduate programs may be more inclined to admit students they perceive as better at mathematics than others. This is institutional screening.

On institutional screening, it is not obvious elite undergraduate colleges are able to distinguish students at this level of mathematical ability given the ACT/SAT censoring, yet higher AMC scores are associated with higher rates of attendance. This is true despite only three colleges having an explicit spot for AMC scores in their applications (MIT, Caltech, and Carnegie Mellon). One simple explanation is that top AMC students signal their ability in their applications, or simply state their AMC scores elsewhere, and admissions committees react to that. It could also be that student's with better AMC scores are better in other ways that are observable to admissions committees. As mentioned previously, this could also be the result of self-sorting; higher performing AMC students may be more likely to apply to elite colleges.

Sorting into STEM majors is likely more due to self-sorting than institution screening because students may select a major without much faculty or school oversight. Unsurprisingly, there appears to be sorting within STEM majors. The average AMC rank of AMC students by major are provided in the final column of Table 7. The three majors with the best AMC performances are Math, Computer Science, and Physics & Astronomy. Additionally, it is worth noting the average rate of earning a PhD varies dramatically by major; 44% of the physics & astronomy AMC students pursue a PhD, while only 1% of those majoring in business, finance, accounting, or marketing do the same.

Ultimately, the economic and scientific impacts of these students depend on their career decisions and opportunities after college. From Table 6, it is clear these students pursue research careers at a relatively high rate, and the estimates in Table 8 suggest their continues to be sorting by math ability even amongst these top students. These statistics and estimates, however, fail to demonstrate to the unique economic and scientific contributions of these students.

To better communicate the economic and scientific contributions of these exceptional math students perform a text analysis on the job titles and company names they list on LinkedIn. 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. For example, the word "data" appears at least once in the job title of 818 individuals in my AMC matched sample. I then count the frequency with which these words appears in the job titles of the individuals in my reference sample. This later count helps me distinguish between words that are generally common in job titles and those that are relatively unique those in the matched AMC sample. I make similar frequency counts for the company names listed on these profiles.

The text analysis reveals these AMC students pursue impressive careers in a diverse set of fields. It indicates top AMC students work in academia, science, technology, medicine, and finance at rates much higher than other college graduates (Table 9). Some of the most common job title words include *professor* (768), *science*/*scientist* (418/682), *research*/*researcher* (647/281), *software* (2,428), *physician* (318), and *trader*/*portfolio* (172/104). The list of company names confirms these

AMC high scorers are most commonly employed by the most innovative and prestigious companies and universities in the world.

The frequency of *cofounder* and *founder* in these job titles hints at the incredible impact some AMC high scorers have had in technology startups. While not all included in this matched sample, Sergey Brin (Google), Mark Zuckerberg (Meta), Peter Thiel (PayPal/Palantir), and Sam Altman (OpenAI) were all AMC high scorers. The scientific and economic value added by these individuals and others like them would be difficult to quantify, but is certainly large.

6 Discussion

Tables

	Never Math League		Ever Math League	
	mean	sd	mean	sd
White Ratio	0.70	0.29	0.73	0.26
Asian Ratio	0.02	0.06	0.04	0.08
Black Ratio	0.10	0.18	0.09	0.16
Hispanic Ratio	0.14	0.22	0.11	0.17
Population (1000s)	55.16	226.26	71.11	205.56
Income per Capita (1000s)	17.43	5.42	20.66	7.95
College Grad Ratio	0.11	0.07	0.15	0.10
Math League Ever	0.00	0.00	1.00	0.00
Math League Active	0.00	0.00	0.21	0.41
Pres. Scholar Candidate	0.06	0.23	0.14	0.34
Pres. Scholar Candidate	0.09	0.49	0.27	0.99
Math League Honoree	0.00	0.00	0.08	0.27
# of Math League Honorees	0.00	0.00	0.27	1.54
AMC 10 Top 3200 Scorer	0.01	0.12	0.07	0.25
AMC 10 Top 3200 Scorers	0.03	0.37	0.20	1.35
AMC 12 Top 3200 Scorer	0.02	0.16	0.10	0.30
AMC 12 Top 3200 Scorers	0.05	0.42	0.27	1.30
Observations	195,183		28,809	

Table 1: This table contains summary statistics for the schools in the high school panel sample by whether or not they ever offer Math League from 1994 to 2020. The sample does not include schools that offered Math League prior to 1994. The sample is made up of 8,296 public, non-magnet, non-charter schools that offer twelfth grade throughout the panel. Of these schools, 1,067 offer Math League at some point during the period and average 5.67 years of participation.

	(1)	(2)	(3)	
	Count Model	Count Model	Count Model	Inflate Model
mathleague_coach	0.128***	0.402***	0.476***	-0.837***
	(0.0294)	(0.0408)	(0.117)	(0.209)
ba_ratio_2000	0	4.645***	7.094***	-9.189***
	(.)	(1.106)	(1.190)	(2.835)
income_2000	0	-0.0000329***	-0.0000340***	0.0000644**
	(.)	(0.0000103)	(0.0000106)	(0.0000290)
log_students	0.108*	0.988***	0.913***	-1.312***
	(0.0595)	(0.102)	(0.171)	(0.298)
api_ratio	5.904***	4.534***	-0.0985	-39.39***
	(2.185)	(0.794)	(3.161)	(10.35)
white_ratio	-0.914*	-0.287	-2.142	-7.430
	(0.545)	(0.711)	(3.174)	(4.889)
Year FE	Yes	Yes	Yes	
Schl FE	Yes	Yes	No	
Technique	OLS	NB	ZINB	
Mean	0.270	0.690	0.270	
N	28809	11259	28809	
Log-Likelihood	-34387.0	-7696.4	-10796.8	

Standard errors in parentheses

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

Table 2: This table presents the a selection of estimated coefficients from Equation 9. The outcome for each of these models is the number of 11th and 12th grade students ranking in the top 3,200 of the AMC 12 A/B. The coefficients of interest are those associated with *mathleague_coach*, which capture the impact of a school hiring or appointing a Math League coach on the number of top AMC scorers. The outcomes for models (2) and (3) are provided in log-odds.

	(1)	(2)	(3)	
	Count Model	Count Model	Count Model	Inflate Model
mathleague_coach	0.00607	0.0222	0.0198	-0.0229
	(0.0271)	(0.0426)	(0.0746)	(0.124)
Year FE	Yes	Yes	Yes	
Schl FE	Yes	Yes	No	
Technique	OLS	NB	ZINB	
Mean	0.270	0.690	0.271	
N	28809	11259	28722	
Log-Likelihood	-34427.3	-7744.2	-9517.3	

Standard errors in parentheses

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

Table 3: This table presents the estimated effect of a school hiring or appointing a Math League coach on the number of top AMC scorers in a placebo exercise. In this placebo test, I randomly assign the sequence of difference-in-difference variables, $math_coach_{st}$, from one school in the sample to another school in my sample. The statistically insignificant results adds further credibility by reducing concerns that the original effects I estimated are actually the result of some uncontrolled, unobservable trends.

	(1)		(2)	
	No HS Math League		HS Math League	
	mean	sd	mean	sd
Male	0.67	0.47	0.67	0.47
White	0.78	0.42	0.72	0.45
API	0.13	0.34	0.19	0.39
Other Race	0.09	0.28	0.10	0.29
HS Cohort	2008.98	7.31	2010.59	5.35
BA Grad Share (2000)	0.25	0.11	0.29	0.12
Income per Capita (2000)	27562.71	11989.24	32327.31	13975.50
AMC 8 Rank	1712.41	1336.90	1800.03	1295.63
Top 3,200 HS AMC	0.13	0.34	0.16	0.37
STEM Major	0.49	0.50	0.52	0.50
Elite BA/BS	0.19	0.39	0.24	0.43
Earned PhD	0.09	0.28	0.09	0.29
Research Career	0.22	0.41	0.25	0.43
Observations	6333		5864	

Table 4: The table provides summary statistics on a sample of AMC 8 high scoring middle school students who have been matched to LinkedIn. Those in subsample (1) attended a middle school in a city where no high school had a Math League coach when the student was in 8th grade, while those in sample (2) attended a middle school in a city where at least one high school had a Math League coach when the student was in 8th grade.

	HS AMC Honoree	HS AMC Honoree	Elite BA/BS	Elite BA/BS	STEM Major	STEM Major
ML_exposure	0.223***	0.226***	0.114**	0.0984	0.0179	0.0104
	(0.0722)	(0.0757)	(0.0548)	(0.0616)	(0.0445)	(0.0511)
amc_nat_rank_1	0.411***	0.410***	0.142***	0.138***	0.0675***	0.0666***
	(0.0193)	(0.0175)	(0.0125)	(0.0125)	(0.00893)	(0.0101)
Mean	0.147	0.159	0.216	0.233	0.501	0.508
Location FE	State	County	State	County	State	County
N	12152	10245	12161	10334	12196	10905
Pseudo R^2	0.125	0.123	0.0713	0.0323	0.0542	0.0481

Standard errors in parentheses

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

Table 5: This table presents the estimated coefficient on $math_coach_i$ from Equation 11 for various student level outcomes. The coefficients on the AMC 8 rank tiers are also provided to add context to the coefficients of interest.

	AMC/LinkedIn Sample		Ref. LinkedIn Sample	
	mean	sd	mean	sd
HS Cohort	2003.60	8.64	2003.60	8.64
Male	0.75	0.43	0.75	0.43
White	0.69	0.46	0.74	0.44
API	0.24	0.43	0.08	0.27
Other Race	0.07	0.26	0.18	0.38
AMC Rank	2,370.69	1651.25	.	.
Elite BA/BS	0.31	0.46	0.02	0.15
Math Major	0.14	0.34	0.02	0.13
STEM Major	0.54	0.50	0.20	0.40
Earned PhD	0.13	0.33	0.02	0.15
Research Career	0.25	0.43	0.05	0.22
Observations	26,664		26,664	

Table 6: UPDATE This table provides summary statistics for the matched AMC student sample. The sample is majority male (72%) and white (65%) or Asian/Pacific Islander (28%). On average, students are from economically advantaged and highly educated hometowns. Unsurprisingly, many of them pursue STEM majors (40%) and attend highly selective colleges (17%). In terms of later-in-life outcomes, 11% of the sample has earned a PhD. This rate is incredibly high, especially when consider around a fifth of the sample is too young to have finished such a degree. In line with this outcome, a large share of these students pursue research careers at a very rate (20%).

	AMC Share	PhD Rate	Avg. AMC Score
Computer Science	0.14	0.11	1,809.69
Math	0.14	0.24	1,848.72
Physics/Astronomy	0.05	0.44	2,115.28
Engineering	0.21	0.16	2,383.96
Chemistry/Biochemistry	0.04	0.30	2,494.33
Bus/Fin/Acct/Marketing	0.11	0.01	2,549.85
Social Sciences	0.14	0.08	2,571.10
Life Sciences	0.07	0.18	2,574.67
Geosciences	0.01	0.14	2,736.13
Observations	26,664		

Table 7: UPDATE

	Elite BA/BS	STEM Major	PhD	Researcher
AMC Rank	0.0870***	0.0676***	0.114***	0.0611***
	(0.0103)	(0.00930)	(0.0140)	(0.0121)
Female	-0.331***	-0.892***	-0.258***	-0.00328
	(0.0376)	(0.0326)	(0.0492)	(0.0357)
API	0.253***	0.0367	-0.303***	0.154***
	(0.0459)	(0.0342)	(0.0549)	(0.0410)
Other Race	0.314***	-0.0811	-0.149*	0.0427
	(0.0530)	(0.0518)	(0.0766)	(0.0559)
Grad Share (2000)	0.138***	-0.0261**	0.00162	0.0254
	(0.0157)	(0.0129)	(0.0186)	(0.0158)
HS Cohort FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Mean	0.310	0.542	0.128	0.251
N	26,664	26,664	26,548	26,659
Pseudo R2	0.0687	0.0561	0.0268	0.0729

Standard errors in parentheses

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

Table 8: This table provides estimates for the coefficients of Equation 12, which is estimated using the matched AMC honoree sample.

Job Title Word	AMC Sample	Ref. Sample
ai	38.3	4.1
analytics	88.9	24.8
candidate	120.8	26.6
cofounder	85.5	1.1
computer	88.1	19.9
counsel	69.4	19.9
cs	56.6	2.6
data	306.8	80.6
fellow	94.5	12.4
founder	85.9	27
machine	52.5	8.6
math	48.4	4.5
mathematics	58.9	5.6
medicine	81	22.1
phd	176.6	13.5
physician	119.3	25.5
physics	40.9	3
portfolio	39	11.6
postdoctoral	37.5	8.6
professor	288	45.8
quantitative	66.4	1.1
research	242.6	63.4
researcher	105.4	12.4
resident	96.4	13.9
science	156.8	46.9
scientist	255.8	35.6
software	910.6	162
sr	121.1	28.9
strategy	91.9	28.5
trader	64.5	1.9

(a) Job Titles

Job Location	AMC Sample	Ref. Sample
amazon	40.5	1.1
amazon web services aws	9.4	0
apple	24.4	.4
capital one	13.5	.4
carnegie mellon university	13.1	.8
epic	15	.4
facebook	28.9	.8
georgia institute technology	9.8	.4
goldman sachs	12	0
google	138.4	3
harvard medical school	9.4	.4
harvard university	18	.8
intel corporation	13.9	.4
jane street	13.1	0
kaiser permanente	9.8	0
lockheed martin	9.8	.8
massachusetts institute technology	18.4	1.5
mckinsey company	9.8	0
meta	24.8	.4
microsoft	39	.4
mit	15.4	.8
northwestern university	10.5	.8
nvidia	9.8	.4
princeton university	15	.8
stanford university	24.8	0
uc berkeley	12.8	.4
university california berkeley	11.3	0
university washington	11.3	0
waymo	9.4	.4
yale university	10.5	.4

(b) Job Locations

Table 9: These tables provide insight on how top AMC scorers are allocated across the economy. The second column in Table 9a provides the number of AMC students out of 10,000 students who have this word in their primary job title on their online profession profile. The third column shows the same frequency for a comparable random sample of online profession profiles. The second column in Table 9b provides the number of AMC students out of 10,000 students who list this employer as their primary employer on their online profession profile. The third column shows the same frequency for a comparable random sample of online profession profiles.

Figures

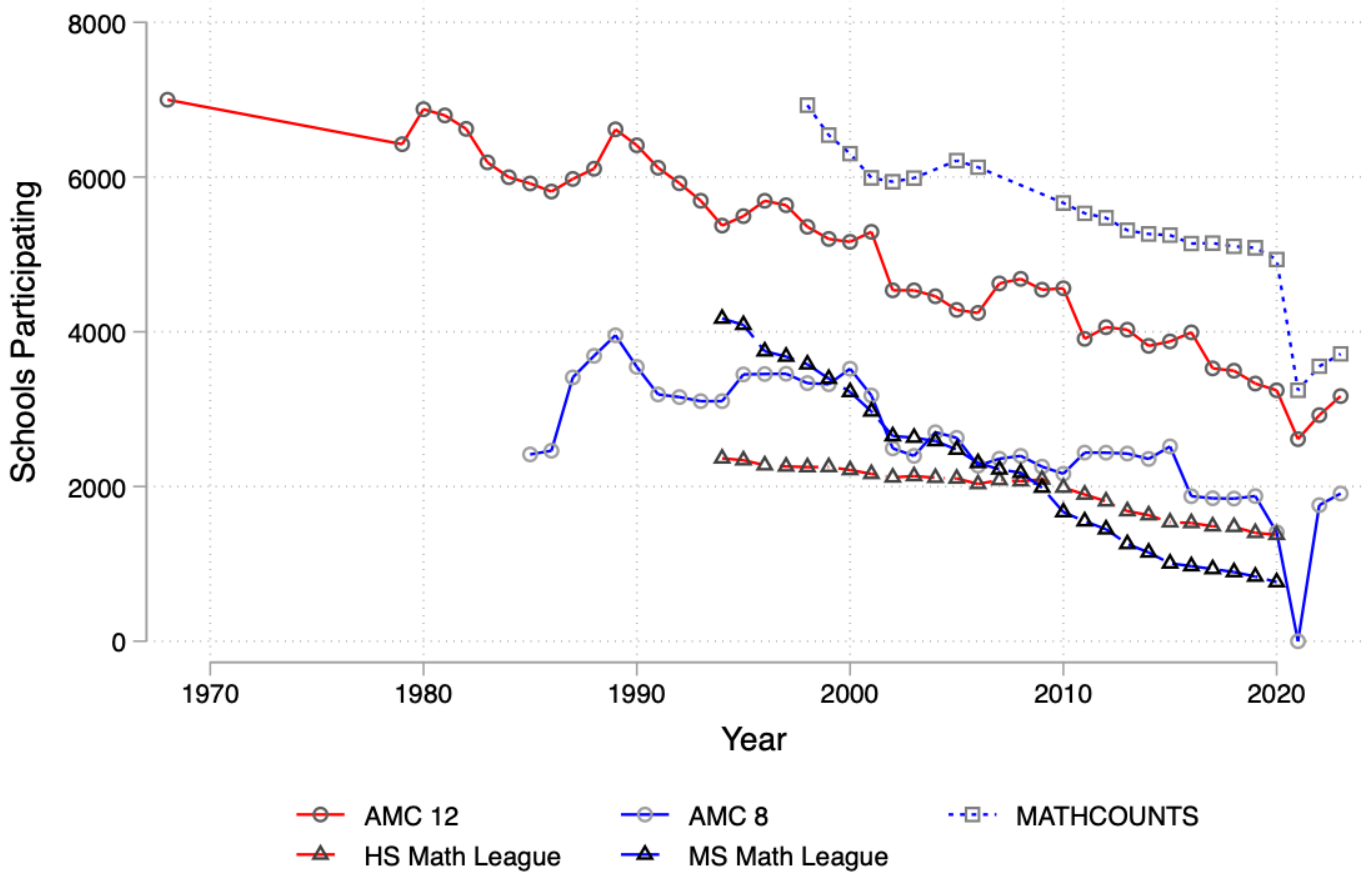


Figure 1: This figure shows the number of US middle schools and high schools participating in various math competitions across years. With fewer and fewer schools participating, there are likely more and more exceptionally talented math students being "missed" by these competitions.

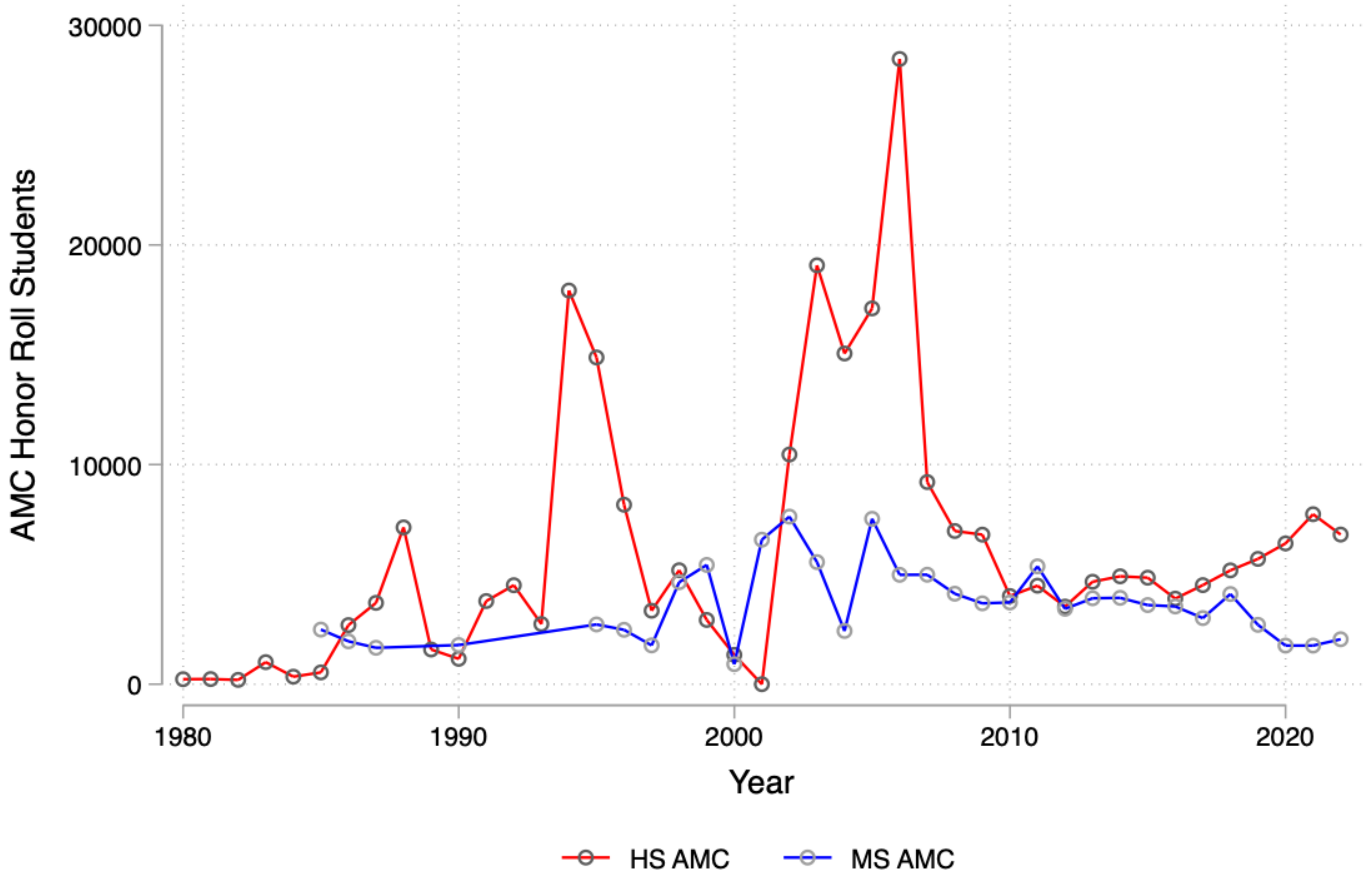


Figure 2: This figures displays the number of observable middle school (MS) and high school (HS) students honored by the AMC each year for their performances. The spikes are driven by shocks in the difficulty of the competitions. The AMC commentaries suggest some of these shocks are intentional while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

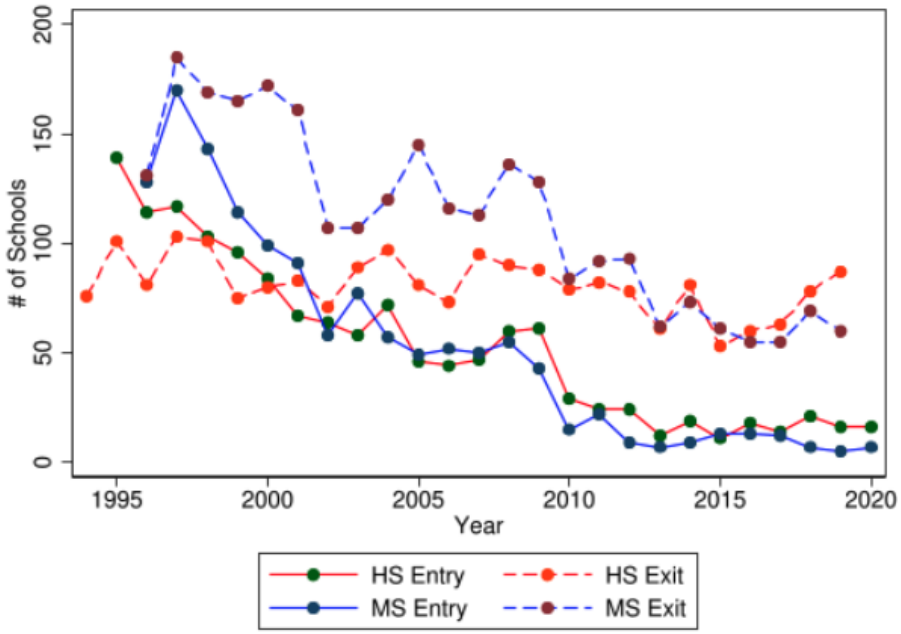


Figure 3: This figure displays the number of schools in the middle school and high school panels joining Math League for the first time or leaving Math Leaguing for the last time for each year from 1994 to 2020. The trend highlights that schools are joining (and leaving) Math League throughout the period.

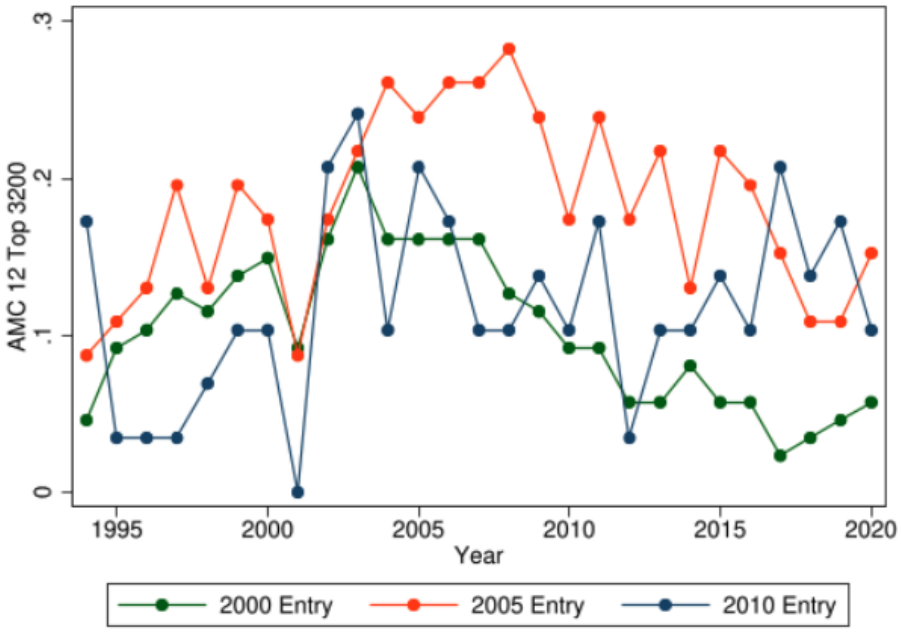
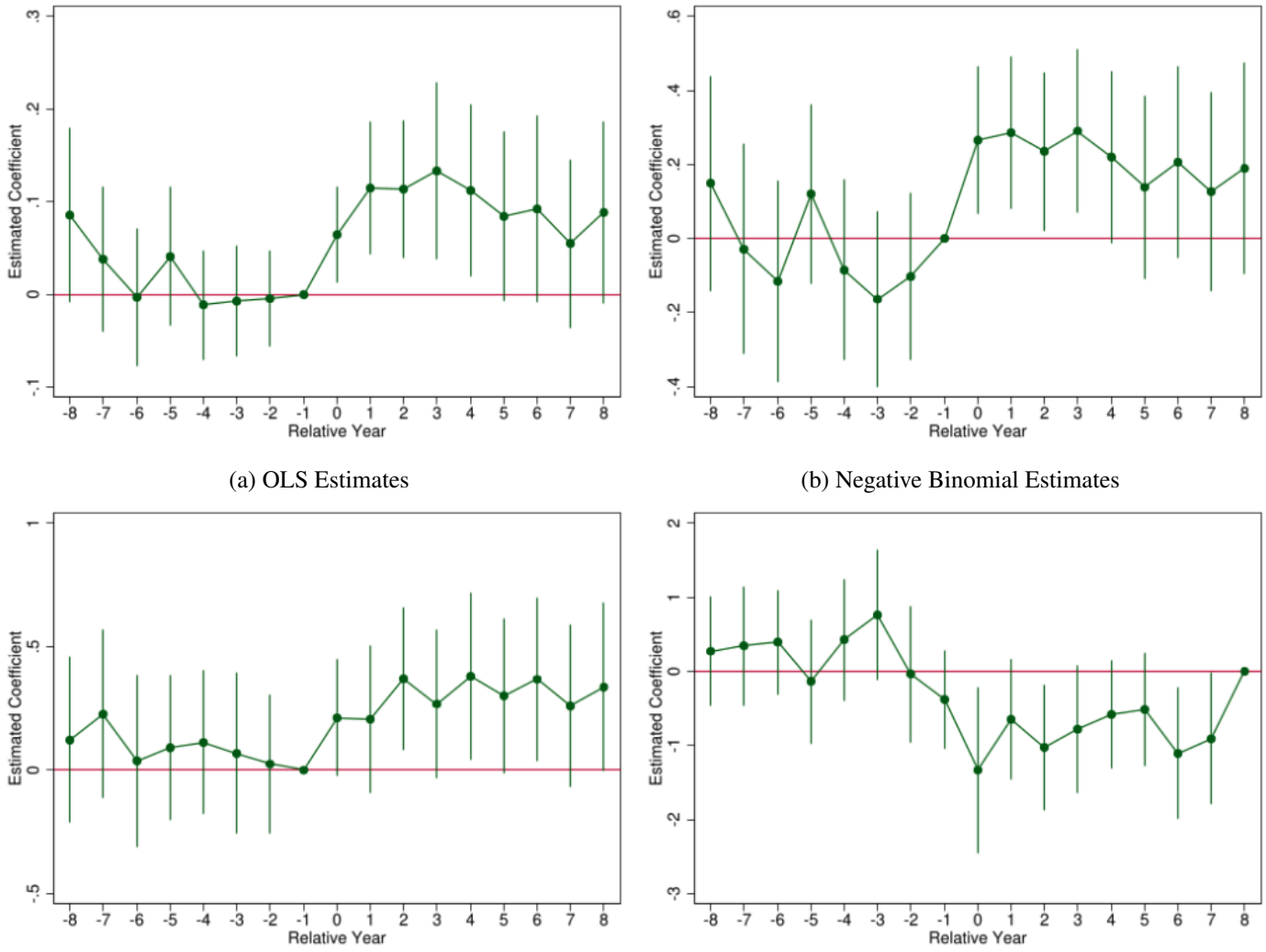


Figure 4: This figure displays the share of schools with at least one top AMC 12 student over the sample period by the year the schools first participated in Math League. For example, this figure indicates that 20% schools that first joined Math League in 2005 had at least one top 3,200 AMC 12 student in 1999. This figure helps demonstrate that many schools participate in the AMC prior to joining Math League.



(a) OLS Estimates

(b) Negative Binomial Estimates

(c) Zero-Inflated Negative Binomial Estimates (Count)

(d) Zero-Inflated Negative Binomial Estimates (Inflate)

Figure 5: These figures display the estimated event study coefficients from Equation 10 with 95% confidence intervals estimated using various methods. The relative year coefficients are centered on the first year schools offered Math League.

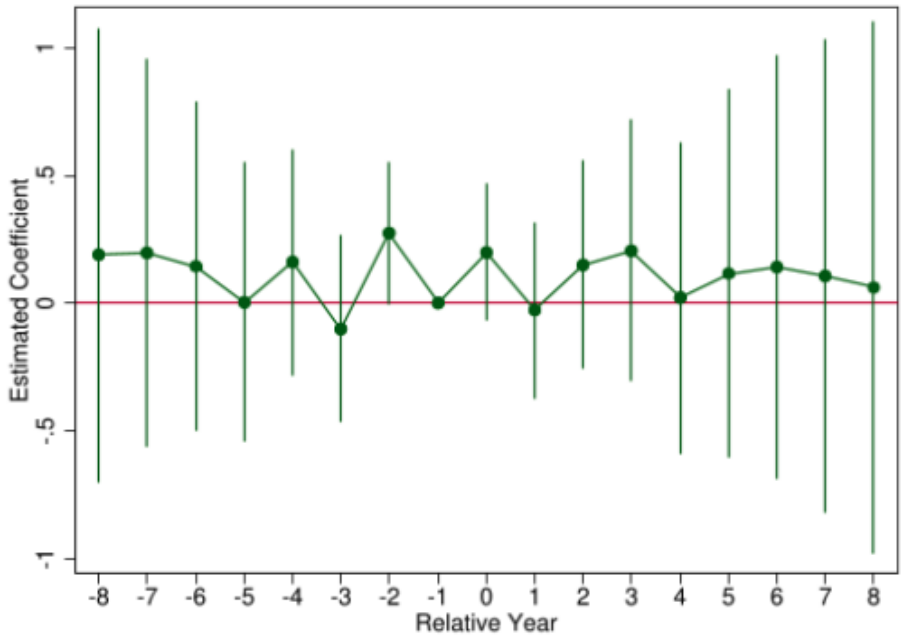
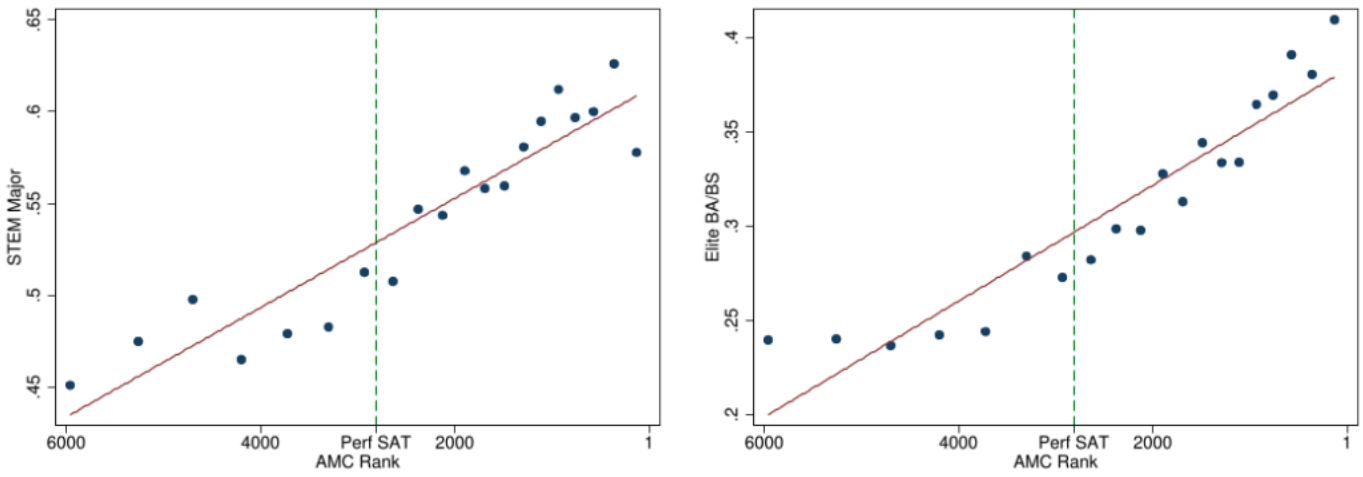
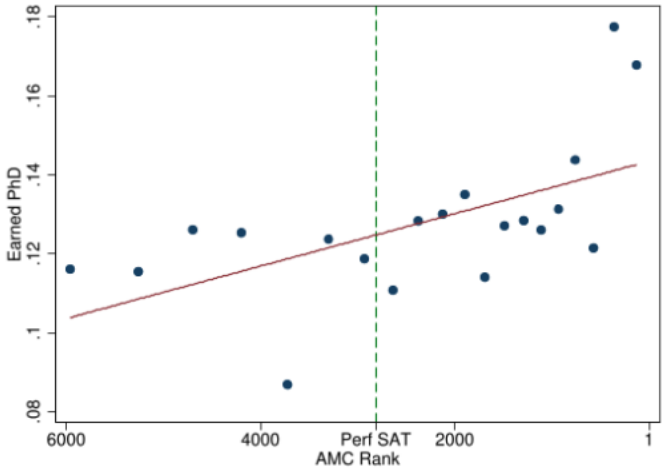


Figure 6: This figure displays the estimated event study coefficients from Equation 10 with 95% confidence intervals for the number of Presidential Scholar Candidates at a school. The relative year coefficients are centered on the first year schools offered Math League. While noisy, the consistency in the point estimates suggest there is no evidence that the timing of a school joining Math League coincided with a shift in the number of generally talented exceptional students.

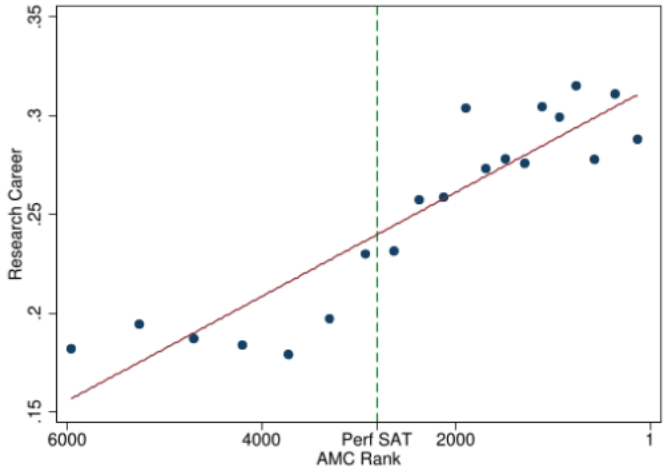


(a) STEM Major

(b) Elite BA/BS

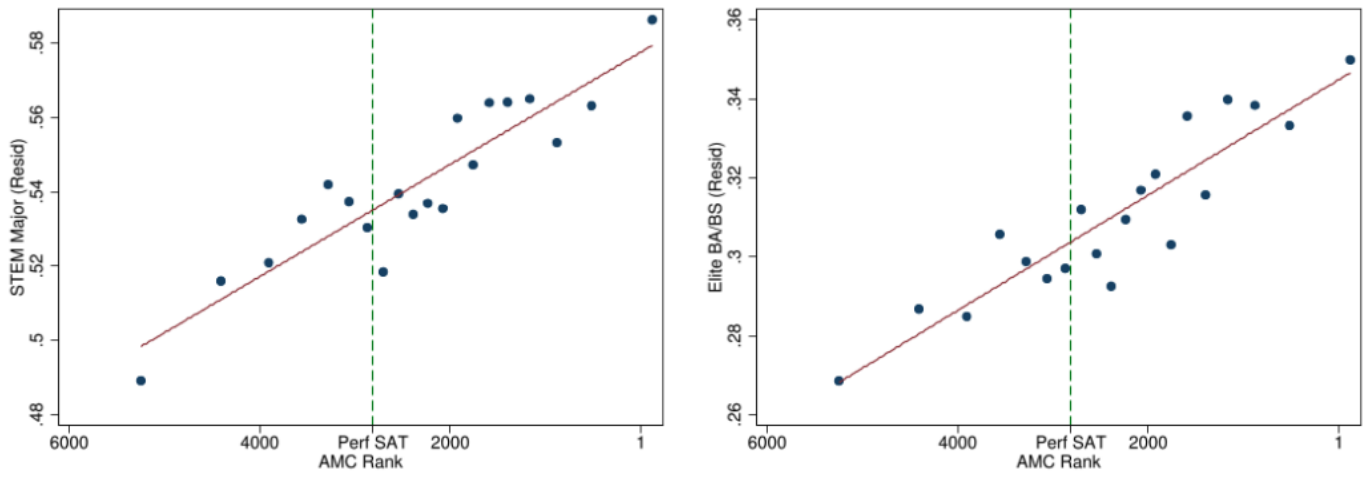


(c) Earned PhD



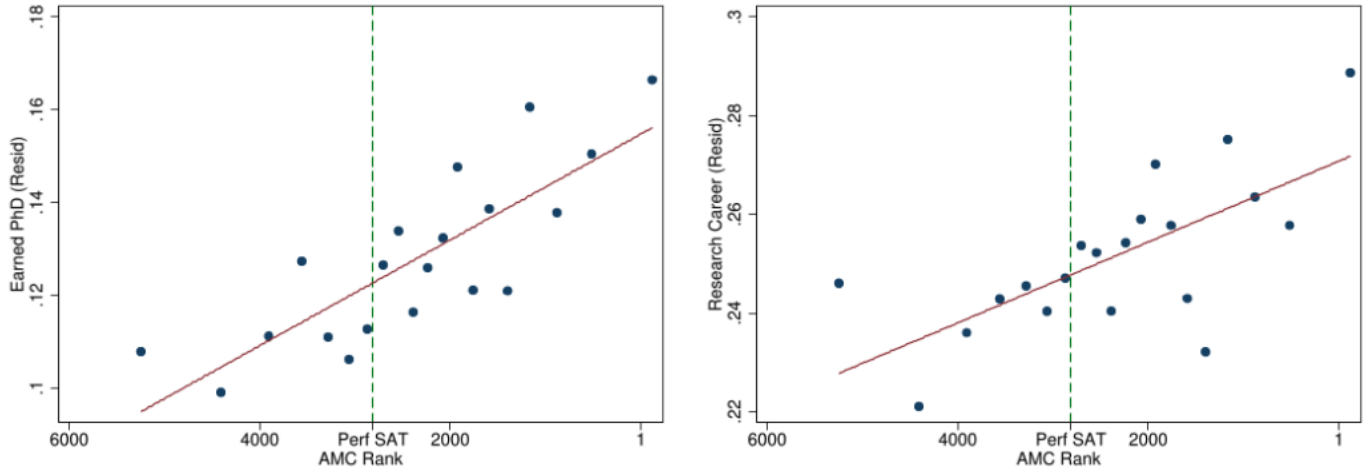
(d) Research Career

Figure 7: Uncontrolled Binscattered



(a) STEM Major

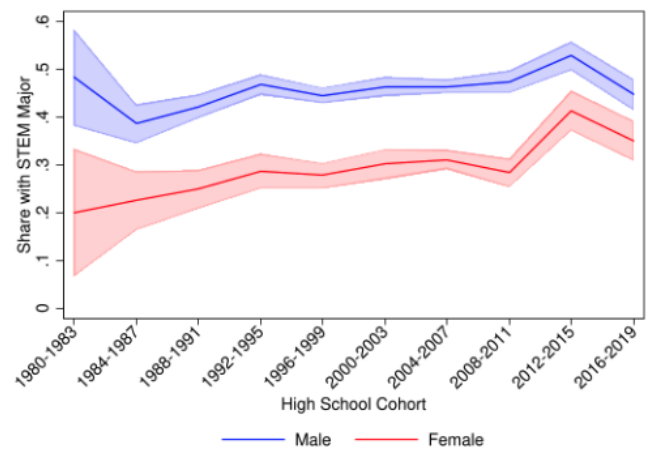
(b) Elite BA/BS



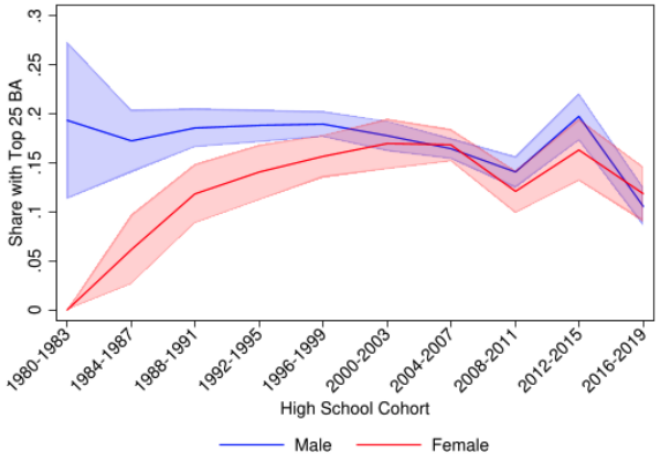
(c) Earned PhD

(d) Research Career

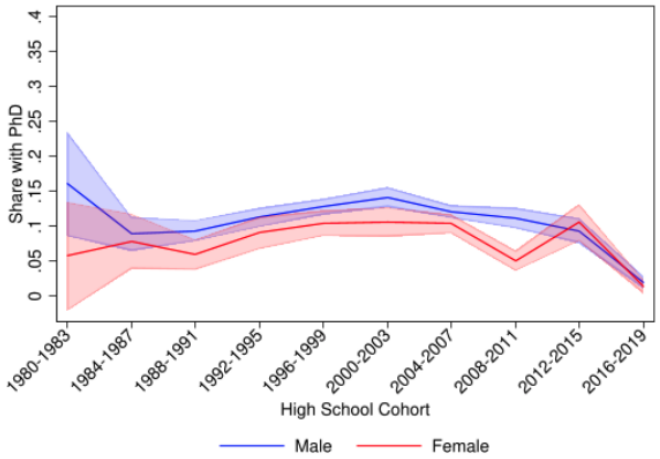
Figure 8: Binscatters with Controls



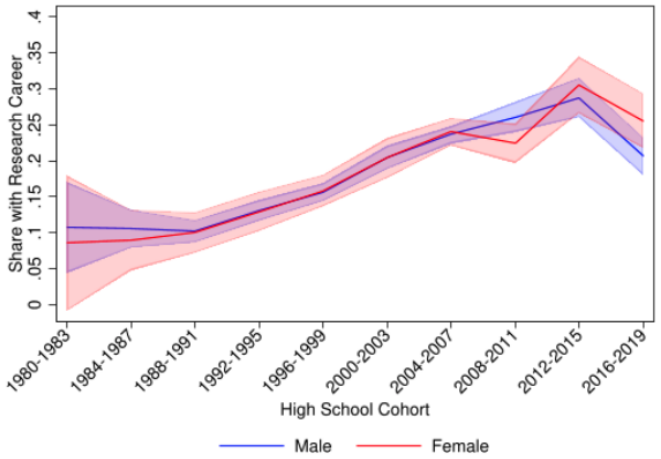
(a) STEM Major Trends by Gender



(b) Top College Attendance Trends by Gender

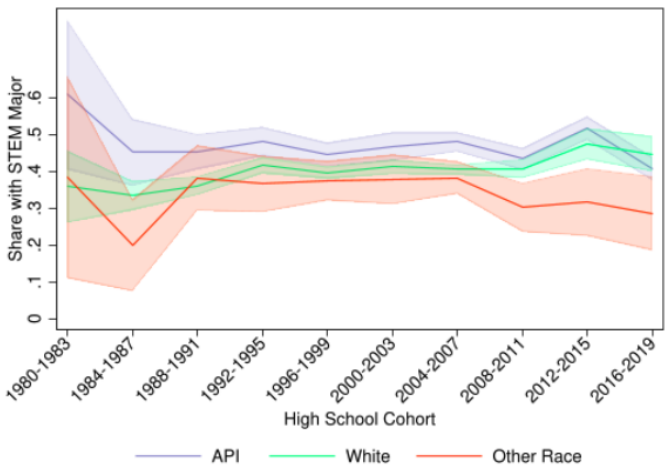


(c) PhD Trends by Gender

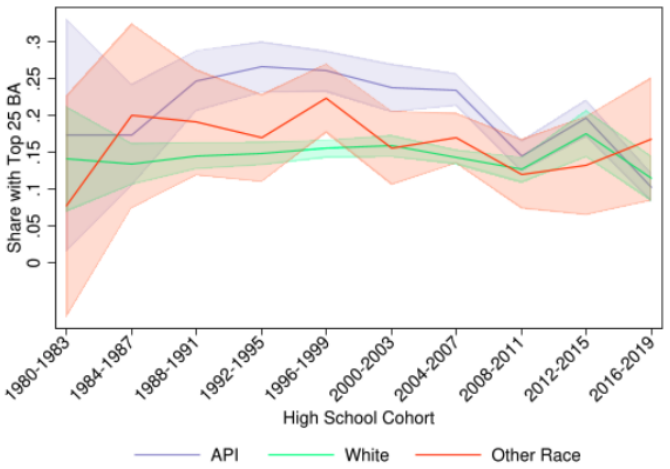


(d) Research Role Trends by Gender

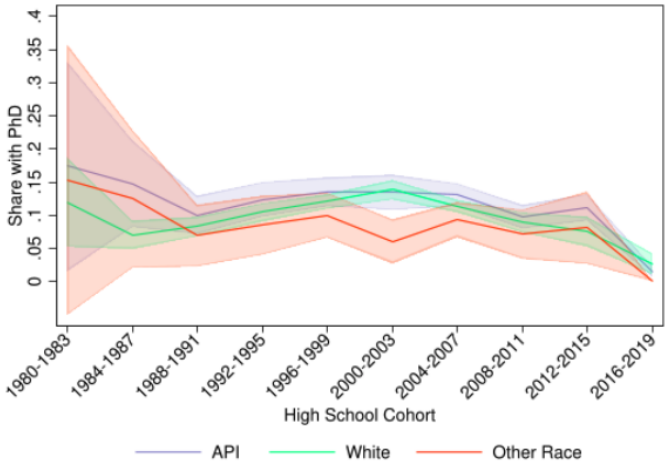
Figure 9: These figures provide time trends for four achievement outcomes by gender from 1980 to 2019.



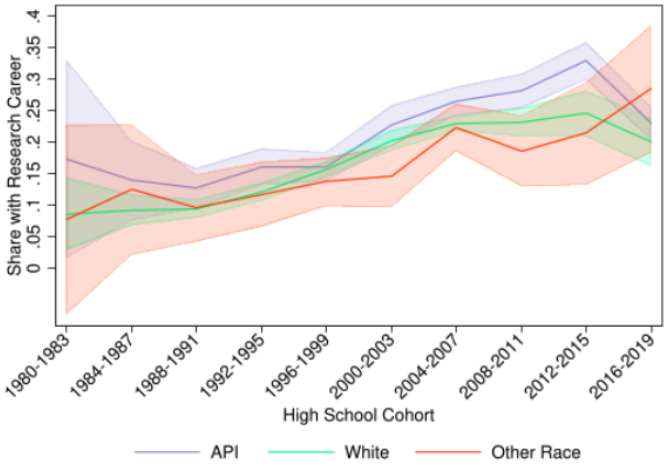
(a) STEM Major Trends by Race



(b) Top College Attendance Trends by Race

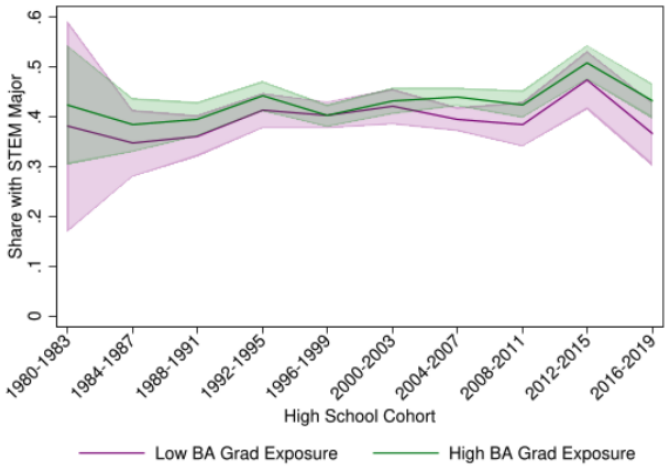


(c) PhD Trends by Race

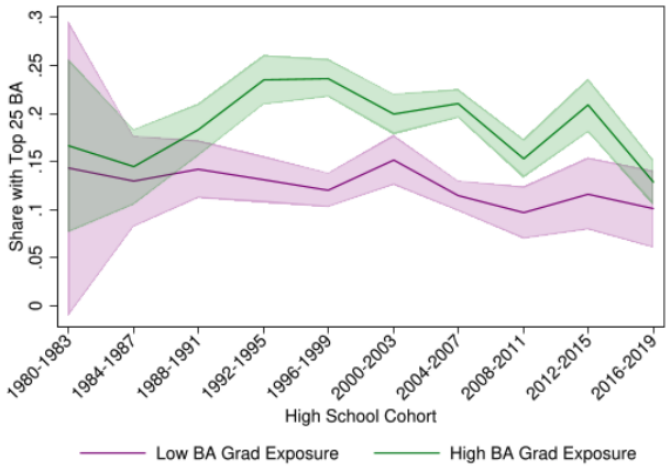


(d) Research Role Trends by Race

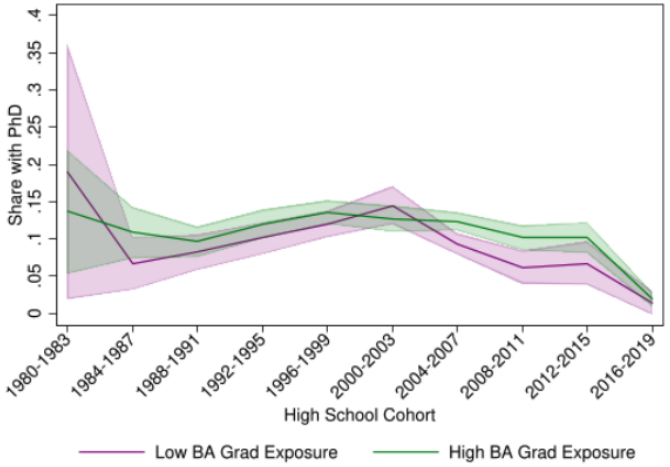
Figure 10: These figures provide time trends for four achievement outcomes by race from 1980 to 2019.



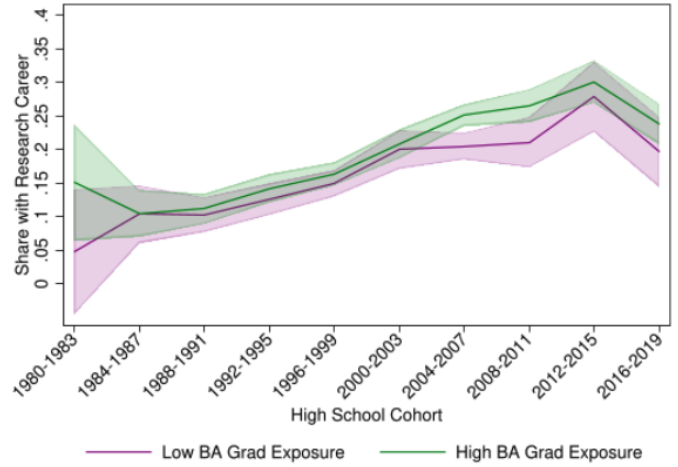
(a) STEM Major Trends by Hometown Income Level



(b) Top College Attendance Trends by Hometown Income Level

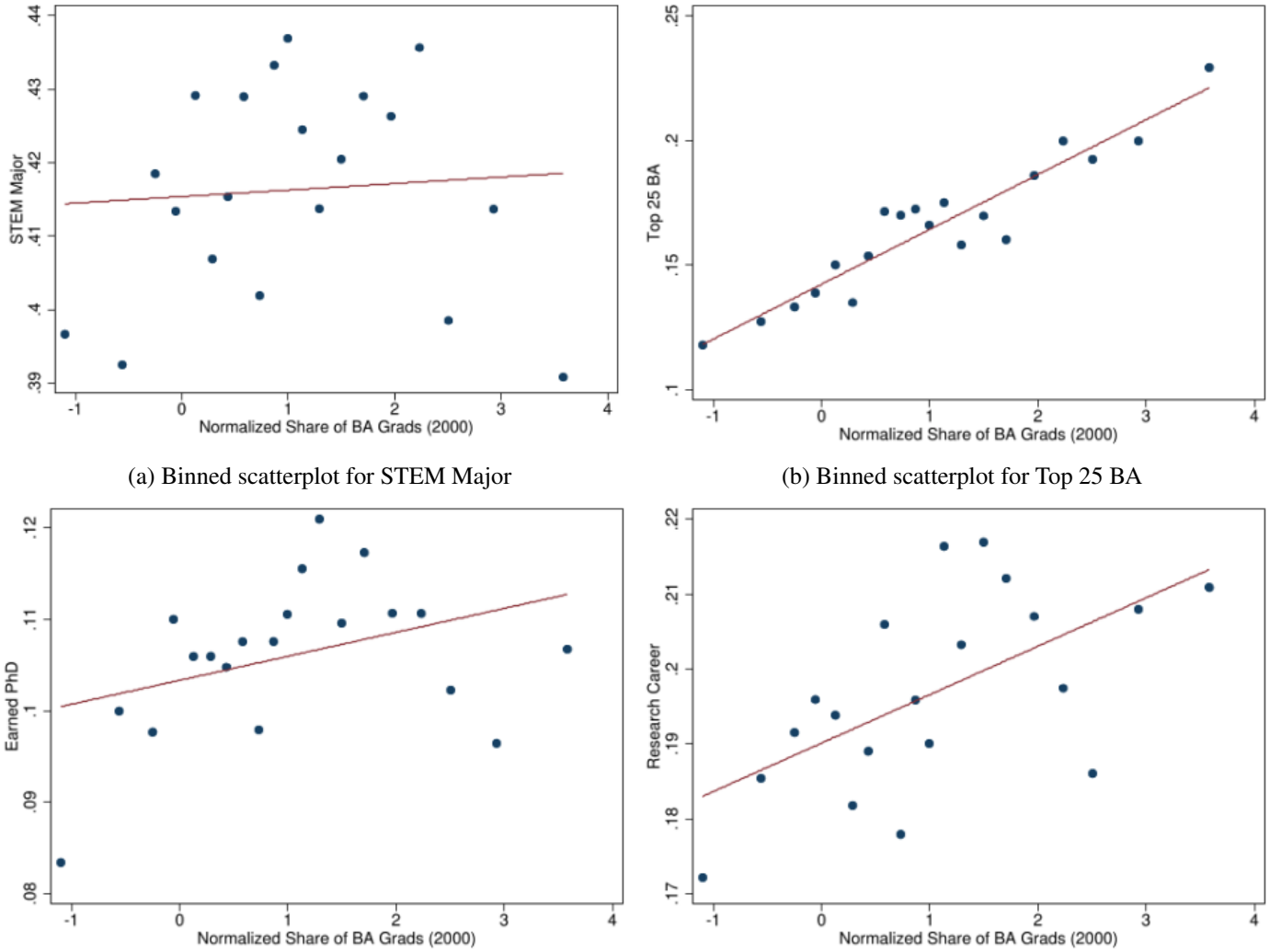


(c) PhD Trends by Hometown Income Level



(d) Research Role by Hometown Income Level

Figure 11: These figures provide time trends for four achievement outcomes by hometown income level from 1980 to 2019.



(a) Binned scatterplot for STEM Major

(b) Binned scatterplot for Top 25 BA

(c) Binned scatterplot for Earned PhD

(d) Binned scatterplot for Research Career

Figure 12: These binned scatterplots document the association between the share of college graduates in an AMC high scorers home town and various later-in-life outcomes.

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