DE GRUYTER OPEN

DOI 10.2478/sbe-2018-0006

OVERCOMING INERTIA WITH A NUDGE: HOW THE AAIMS PROGRAM INCREASED ADVANCED PLACEMENT PARTICIPATION IN ARKANSAS

HOLT Andrew
Miami University, USA

McGARRITY Joseph
University of Central Arkansas, USA

Abstract:

The Arkansas Advanced Initiative for Math and Science (AAIMS) is program with the goal to increase Advanced Placement (AP) participation and increase the passing rate of AP exams. The program offers monetary incentives and support to students and teachers for one year, effectively creating a natural experiment. This paper exploits the one year treatment to empirically show that the program is effective at increasing a school's AP participation rate by nudging the schools to increase AP offerings and satisfying a latent student demand for AP classes.

Key words: *AAIMS, Advanced Placement Participation, Advanced Placement Incentives*

1. Introduction

College is one of the best methods for promoting upward social mobility. People with college degrees tend to earn higher incomes. Unfortunately, the six-year college graduation rate is only 39.7 percent in Arkansas, which is worse than every other state except Alaska. If Arkansas could increase the college graduation rate, then its people could earn higher incomes.

Arkansas's low college graduation rate is in part due to inadequate college preparation in Arkansas high schools. Increasing Advanced Placement (AP) course participation and AP exam taking has become one of the main strategies employed by numerous states to better prepare high school students for college. Generally, students who take AP courses in high school are more likely to graduate from college (Dougherty 2005).

Many state and federal government organizations have implemented a diverse set of programs and policies to increase AP participation. Programs range from either focusing on increasing student demand for classes or increasing the supply of classes offered to students. Programs focused on increasing the demand for AP classes emphasize giving students direct incentives such as money for classes or guaranteeing college credit upon completing a class. Programs and policies focused on increasing the supply of classes tend to concentrate on paying teachers, providing support and resources to teachers, or mandating a minimum number of AP classes offered. Most studies do not offer clear answers to whether the causes of increased AP participation is due to an increased supply or increased demand.

The Arkansas Advanced Initiative for Math and Science (AAIMS) AP incentive program is a perfect natural experiment because monetary incentives only last for one year. During that year, the AAIMS program also bore one year costs that limited the supply of AP classes. AP participation in schools went up after joining the AAIMS program and stayed high even after the monetary incentives for students were taken away suggesting that the increase was most likely caused by AAIMS providing the necessary momentum to clear the one year hurdles and increase the supply of classes. Once AAIMS bore the one year costs, schools tended to keep offering AP classes on their own. AAIMS provided the necessary momentum and resources to battle AP inertia in schools. There was latent demand for AP classes among Arkansas students that was left unsatisfied because of supply constraints. Because demand for AP classes is latent, policy should concentrate on alleviating constraints that tie down the supply of AP classes.

2. Program Overview and Literature Review

In 2007, Arkansas was one of several states that received a grant from the National Math and Science Initiative (NMSI) to improve mathematics and science education. Arkansas Advanced Initiative for Math and Science (AAIMS) is the affiliated institution that manages the NMSI's College Readiness Program for Arkansas. The AAIMS program is modeled after the Advanced Placement Strategies program in Texas. The goal of AAIMS is to 1) increase the number of students taking AP courses and 2) increase the number of students scoring a 3 or higher on AP math, science, and English exams.

AAIMS provides teacher support, student support, and monetary incentives to achieve its goals. AAIMS provides monetary rewards to students, teachers, and schools based on students AP examination performance. Students received $100 for every exam score of at least three. Teachers also received $100 for every student that made a three or above on the AP exam. AAIMS also provides free professional workshops for AP math, science, and English teachers and extra tutoring and study sessions for students in AP math, science, and English courses. They also pay for students to take AP exams and provide equipment and supplies to students. The

AAIMS program limited monetary rewards, teacher workshops, and student studying sessions to eleven AP courses and exams in Math, Science, and English.

The AAIMS program is implemented as a natural experiment. AAIMS only accepts about ten schools per year into the program. The first cohort of schools was admitted into the AAIMS program in the 2008-2009 school year, the second cohort was admitted the next year, and so on. The program focuses most of its attention to the newly added schools. Student cash rewards for passing AP exams, Saturday school funding, and free professional workshops for teachers were all offered during the first year of the program. While AAIMS schools still have access to workshops in the later years, it is up to the school to provide their own funding for Saturday schools and for teachers to attend these workshops.

The AAIMS program is a natural experiment in which the policy's influence on student demand is limited to one year. Because AAIMS only offered monetary incentives to students and teachers for one year, the increased student demand for AP classes should be temporary. Because AAIMS paid for the one year cost to get teachers certified to teach AP classes, schools continued to offer AP classes after their funding dried up.

To date, the AAIMS program has not received scholarly scrutiny. This paper is the first examination of the program that we am aware of. The work most closely related to this paper is a series of papers by Dr. Kirabo Jackson (2008, 2010a and 2010b) who analyzed an AP incentive program in Texas organized by Advanced Placement Strategies (APS). Jackson finds that the APS program has a positive effect on AP participation rates. Jackson's investigation suggests that student and teacher monetary incentives cannot explain the increase in AP participation by themselves. He suggests that low AP participation is not only due to low student demand for AP classes; instead, AP participation is also hampered by administration policies and school norms that unintentionally limit a student's opportunity to take AP classes.

3. Data

The data for this analysis comes from a combination of two separate datasets that were combined together to create a useable dataset. The data for school demographics comes from the University of Arkansas's Office for Education Policy. The dataset extends back to the 2004-2005 school year, four years before the AAIMS program began, and progresses to the 2012-2013 school year, when cohort 5 joins the AAIMS program. The school demographic data is publically available through the Arkansas Department of Education. The second database on school AP participation levels comes directly from the Arkansas Department of Education. In the combined dataset, if any school observation had missing control variables, the school's data from that year was deleted from the dataset. Sometimes school's had missing yearly observations because during the nine years of data available, some schools were shut down and students were bussed to other high schools, effectively merging the schools. Merged schools are thought of as completely different schools by the Arkansas Department of Education because the student and teachers are integrated with other large number of students and teachers. This dataset is unbalanced in the sense that all schools do not have the same number of observations due to missing control variables or the school being merged. A second combined dataset was constructed that is balanced by deleting all schools that had one or more year of missing data. We estimate the models on both the balanced and unbalanced data sets.[i]

4. Empirical Models

We use two identification strategies in order to extract the effect of the AAIMS program on the AP participation rate. The first model uses a fixed effects strategy to estimate the percent of a school taking AP classes. The second model uses a first differenced strategy to estimate the yearly change in the AP participation rates.

A. Model 1: Fixed Effects

Model 1 estimates the effects of AAIMS and other variables on the AP participation rate for school *i* during time *t* the form below

[1] $\%AP_{it} = F(AAIMS_{it}, \text{School Demographics}_{it}, \text{School Fixed Effects}_{it}, \text{Year Effects}_{it})$

There are 5 AAIMS variables in total. The AAIMS variables establishes 1) if a school is in the AAIMS program and 2) how long the school has been in the AAIMS program. AAIMS 1 signifies that the school is in its first year of the AAIMS program and AAIMS 5 signifies that the school is in its fifth year of the program. This allows us to track the effect of AAIMS across time. It should be noted that AAIMS 2-5 variables do not capture the effects of that single year in the AAIMS program, but captures the AP activity that occurs in that year but which was also influenced by exposure to the AAIMS program in previous years. For instance, a school with AAIMS 3 variable would have already had the effect of AAIMS for two years already and this would show in the coefficient. [ii]

We also employ eight control variables in the model. The natural log of the total number of students enrolled at a high school. %Black and %Hispanic are the percentages of students that identify as African-American or Hispanic, respectively. %Other is the percentages of students that do not identify as either African-American, Hispanic, or White/Caucasian. %GT is the percentages of students that are identified as Gifted and Talented or “Advanced.” Gifted and Talented students are highly encouraged by school administrators and GT coordinators to enroll in AP courses. %SpecialEd is the percentage of students that have been identified with learning disabilities. %LEP is the percentage of students that have been identified with limited English proficiency. The Poverty Index aggregates and scales different poverty measurements in a school’s district that make it easier to compare the level of poverty between schools. We also include individual school fixed-effects which captures the difference between individual schools. The year fixed-effects capture any aggregated fluctuations in AP participation. The fixed effects give each school and year a unique intercept. Descriptive Statistics for these variables and other outcome variables can be found in Table 1.

B. Model 2: First Differences

The second model used is an OLS, which uses differenced data, in the form below

[2] $\Delta\%AP_{it} = F(AAIMS_{it}, \Delta \text{ School Demographic}_{it}, \Delta \text{ Year Fixed Effects}_{it})$

The AAIMS variables work a little different in model 2 than they do in model 1. The AAIMS variables still establishes 1) if a school is in the AAIMS program and 2) how long the school has been in the AAIMS program. AAIMS 1 signifies that the school is going into its first year of the AAIMS program and AAIMS 5 signifies that a school is going into its fifth year of the program. We still are able to track the effect of AAIMS across time. However in model 2, the AAIMS 2-5 variables only capture the effect of the AAIMS program from the previous year into the present year. There is no "building on top of" the earlier years of the program in Model 2. Each AAIMS variable in model 2 only captures the effect of an AAIMS school moving into the specific year of the program. This is because the data is differenced before running the OLS regression.

The eight control variables are also differenced and a school's observation shows how the variable changed from one year to the next. The school fixed-effects dummy variables became zero when they are differenced so they are not included in the estimate. We've included dummy variables for the changes in years to capture any policy difference Arkansas may have imposed onto all schools.

5. Results

A. Main Results

Table 2 shows the results of model 1 and model 2 on both the balanced and unbalanced data sets. Columns 1 and 2 report the fixed effects estimates, while columns 3 and 4 report estimates from the differenced model. Columns 1 and 3 report estimates from the unbalanced dataset, while columns 2 and 4 report results from the balanced dataset.

All the AAIMS variables in the fixed effect regressions are significant at the .05 level and the coefficients increase with each consecutive AAIMS variable. This shows us that AP participation tends to increase as a school is in the AAIMS program longer. Even though the AAIMS 2 coefficient is larger than the AAIMS 1 coefficient, the AAIMS 2 coefficient is also capturing the AAIMS 1 coefficient because schools that are in the second year of the program have also been in the first year of the program. The coefficients indicated that most of the benefit of being in the AAIMS program comes in the first year and increases in AP participation in the later years is smaller. Most of the support from AAIMS comes in the first year and after the first year the support is scaled back for a school. The continued statistically significant coefficients of the AAIMS variable shows that even after the AAIMS program is scaled back at a school, the increases that the school had remains. The AAIMS program has a lasting effect on schools. Note that the results hold for both the balanced and unbalanced datasets.

Next consider the results from the differenced equation, only the first two AAIMS variables in the first differenced regression are statistically significant at the .05 level. The coefficients of the first two AAIMS variables are positive showing that entering into the AAIMS program and going into the second year of the program substantially increase the percent of students in a school taking AP classes. The coefficients of AAIMS 3, 4, and 5 are positive and not significant, suggesting that the gains from the first two years are intact and no additional changes occur from partaking in the program after two years.

All of the percent SpecialEd and the Poverty Index variables were significant at the .05 level and they moved in expected directions in the fixed-effects and differenced models. All of the percent GT variables moved in the expected direction and were significant in the fixed-effects model. The R-squared for the fixed-effects model on the unbalanced and balanced datasets were 0.696 and 0.706, respectively.

Taking both models into consideration, we find that the AAIMS program is associated with increases in a school's AP participation rate during the first two years of the program and the increases tend to last even as support is scaled back.

B. AP Participation Split Regressions

Next, we split the dataset into subsets to see if the general results hold under different circumstances. Our first criterion for splitting the data is based on the notion that the AAIMS program might have different effects depending on how big the AP program is at a particular school already. We averaged the AP participation rate for schools in the four years before any school was admitted into the AAIMS program. We then ranked the schools from largest to smallest based on these four year averages. We split the data equally into three subsets where the first subset contained the top third of schools based on AP participation, the second subset contained the middle third of schools based on AP participation, and the third subset contained the bottom third of schools based on AP participation. We then utilized the fixed-effects model and the differenced model on each subset individually.

The results for the split AP regressions are found in Table 3. We find that all of the AAIMS variables are positive and statistically significant in the fixed-effect models. We also find that the first AAIMS variable is positive and statistically significant in the differenced model. Splitting the data based on AP participation tells a similar story as the original dataset, the AAIMS program is associated with an increase in AP participation in the first year of the program and the gains from the program tend to be lasting.

The benefit of splitting the regression is that it allows the coefficients for the AAIMS program to vary depending on whether or not the individual school is in the top, middle, or bottom thirds of schools based on AP participation. Note that the AAIMS program has larger effects if the school was in the bottom subset. The AAIMS program has larger impacts on schools with low AP participation. It should be noted that AAIMS schools in the top third of schools based on AP participation do not see the massive increases that is seen in the other subsets. The results in Table 3 suggest that the AAIMS program has a bigger impact if the AP participation is low, compared to schools with well-established AP programs, before the AAIMS program is introduced. Schools that have well-established AP programs with a large AP participation rate don't have as much room for improving their programs as schools with low AP participation rates.[iii]

C. Enrollment Split Regressions

The second method of splitting the data was based on school enrollments; we wanted to know if AAIMS had stronger or weaker effects for bigger or smaller schools. Again, we averaged the enrollment for each school in the four years before any AAIMS treatment, ranked them, and then split them in thirds based on their rank. We then applied the fixed-effects and differenced model to the three subsets.

The results from the second split method are summarized in Table 4. These equations tell a similar story to our main results and the results from the splits based on AP participation. AAIMS is associated with an increase in AP participation in the first year and the gains don't drop off. The AAIMS's variables in column 11 and 12 are all positive and significant. The AAIMS's variables for column 13 are positive but insignificant, but there is only one school in that particular subset.

In the differenced datasets, the AAIMS1 variable in column 14 and 15 are both positive and significant signifying that the AAIMS program increase AP participation in the first year for both large and middle sized schools. Again, by splitting the data, it allows the coefficients for the AAIMS variables to change depending on the size of the school. Note that the AAIMS coefficients, in both the fixed-effects and differenced equations, are larger in the middle-sized schools than the bigger sized schools. However, the AAIMS 2 variable is the only significant in the top third of schools based on enrollment in the differenced datasets. Splitting the data based on enrollment sizes suggests that the AAIMS program has a larger impact on middle sized schools compared to bigger sized schools.

By splitting the data under two criterion, AP participation and school enrollment, we investigate whether or not the main results hold under these extreme circumstances. Again, we find that the AAIMS program is associated with an increase in AP participation in the first year of the program. The increases tend to last over time, even as support for AP course at a school is decreased. We find that the AAIMS program has lasting and positive effects on AP participation.[iv]

D. AP Classes per School Enrollment

Lastly, we investigate whether students had a latent demand for AP classes. Because the increases in AP participation from the AAIMS program outlasts the monetary incentives given to student and teachers, we believe that the monetary incentives are not what is driving the AP participation increases. If students were responding to monetary incentives, then their behavior should return to pre-AAIMS levels when the monetary incentives are taken away; which did not happen. The increase in AP participation is not due to an increase in student demand for more AP classes.

Next we substitute change in AP participation, our dependent variable, with the change in the number of AP classes offered per school enrollment in our differenced model. The purpose of this is to see if the number of AP classes per school enrollment increased when the school first joined the AAIMS program. The results are shown in Table 5. We find that the AAIMS program is statistically significant in increasing the number of AP classes offered per school enrollment in the first year. Because there is no statistically significant negative coefficient after the AAIMS 1 variable, we conclude that the increase in AP classes remained after the first year of the program. We find that there are more AP classes available to students after joining AAIMS. Because the AP participation increases in unison with the increase in AP classes per enrollment, and when monetary incentives are taken away students don't stop taking AP classes. It seems that the increase in AP participation is due to increased opportunities for students to take classes.

6. Discussion and Conclusion

The main insight from the results is that a one year program such as AAIMS can increase AP participation permanently by overcoming hurdles that cause school inertia. We find that schools with low AP participation rates tend to see the biggest increases in the participation rates, suggesting that schools that do not have established AP programs see the most benefit from AAIMS. In general, schools that do not have a culture of AP participation see the greatest gains from the program. Also, medium sized schools tend to see bigger increases in AP participation than large schools. We also find that AAIMS is associated with increases in AP classes offered per school enrollment signifying that schools increase AP classes when they join AAIMS. Increase AP participation is associated with an increase in monetary incentives for students and an increase in AP classes; however, a decrease in monetary incentives does not reduce AP participation. It should be noted that the monetary incentives for students were only rewarded if students passed an AP exam. Student demand for AP classes did not increase because students were uncertain if they were going to receive the incentive after taking the class. We show that the increase in supply of AP classes is the main cause of the increase AP participation.

Still, the most interesting insight from the results is that both AP participation and number of AP classes per enrollment can be increased with a one year program. Schools face infinite ways to allocate their scarce resources. If higher AP participation is a favored policy by a state, then a program like AAIMS can change a school's budget allocation preferences by simply nudging them in the preferred direction. In general, schools that did not have a culture of AP participation saw the greatest gains, suggesting that these schools were undervaluing AP classes and not satisfying latent demand. Nudging schools to put more emphasis on AP allocation led to lasting positive effects by concentrating on incentivizing teacher and administrators as well as taking on the costs to get teachers certified to teach AP classes. The AAIMS nudge changed the school's behavior, effectively overcoming school inertia, as schools offered more AP classes to their students even after AAIMS retracted support. The increase access to AP classes allowed more students to take AP classes which increased the AP participation rate.

References

Dougherty, Chrys, Lynn Mellor, and Shuling Jian, (2006), *The Relationship between Advanced Placement and College Graduation*, 2005 AP Study Series, Report 1." National Center for Educational Accountability,1-35.

Jackson, C. Kirabo. (2008), *Cash for Test Scores: The Impact of the Texas Advanced Placement Incentive Program*, Education Next, Vol. 8, no. 4, 70-77.

Jackson, C. Kirabo. (2010a), *A Little Now for a Lot Later A Look at a Texas Advanced Placement Incentive Program*, Journal of Human Resources. Vol. 45, no. 3, 591-639.

Jackson, C. Jackson, (2010b), *The Effects of an Incentive-Based High-School Intervention on College Outcomes,* NBER Working Paper No. 15722, Vol. February, 1-50.

[i] Sometimes schools would become "New Technical High Schools". Becoming a "New Tech High School" would change the official name, the school identification number, and some school goals, but there was no change in administration or student demographics. We changed the names of the high school back to the original name and treated the schools the same in the regressions.

[ii] Because of the rolling out of the program over time, the number of AAIMS cohorts available for AAIMS estimations decreases for each consecutive AAIMS variable. The AAIMS 1 variable has observations from all five cohorts. The AAIMS 2 variable only has observations from the first four cohorts. The data does not extend far enough to allow the last cohort to obtain AAIMS designation for a second year.

[iii] We ran a Chow Test on both the fixed-effects data and the differenced data to test whether the coefficients of the AAIMS variables were statistically equal among the split subsamples. The computed F value for the fixed-effects equation did not exceed the critical value and the computed F value for the differenced equation did exceed the critical value. We also used interaction terms in the fixed-effects equation to test if the coefficient of each variable was equal between the splits. We reject the hypotheses that the coefficients between the split AAIMS variables are equal to one another. We conclude that AAIMS has stronger and weaker effects on schools based on the AP participation rate before the school received AAIMS.

[iv] Again we ran a Chow Test on both equations to test whether the coefficients of the AAIMS variables were statistically equal among the split subsamples. The computed F value for the fixed-effects equation did not exceed the critical value and the computed F value for the differenced equation did exceed the critical value. We also used interaction terms in the fixed-effects equation to test if the coefficient of each variable was equal between the splits. We reject the hypotheses that the coefficients between the split AAIMS variables are equal to one another. We conclude that AAIMS has stronger and weaker effects on schools based on the size of the school