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Abstract

This paper analyzes the effect of a statewide merit-based scholarship program on educational outcomes in Arizona. It tests whether Arizona's Instrument to Measure Standards (AIMS) scholarship has an effect on a comprehensive set of educational outcomes such as the number of applicants, student admissions, first-year first-time enrollment, ACT scores of entering freshman, retention rates, as well as on the level of tuition and fees at the three schools targeted by the program; Arizona State University, University of Arizona and Northern Arizona University. Both difference-in-differences estimation as well as synthetic control methods shows that AIMS has an economically and statistically significant effect on many of these outcomes, primarily enrollment and tuition. Enrollment effects are greatest among African American and Hispanic students and are significant for both men and women.

1 Introduction

In the United States, the federal and state governments spend billions of dollars on higher education each year.[1] Many of these dollars are funneled into federal programs such as Pell grants, Perkins loans, Stafford loans, and college student tax credits for higher education expenses. The effectiveness of different types of student aid on an array of outcomes has been extensively studied (Dynarski, 2004; Bettinger, 2004; Avery and Hoxby, 2004).

Over the past two decades, individual states in the U.S. have created their own statewide merit-based scholarships to encourage residents to attend colleges and universities in their home states (Dynarski, 2004).[2] While not a single statewide merit-based scholarship existed before 1991, today there are at least 15 states that provide merit-based scholarships for their residents.[3]

Many politicians have touted these programs as successful, yet there are many important questions that need to be answered.[4] Do these scholarships increase the probability that high school students will attend college? How do students respond to merit aid compared to need-based aid? Do these scholarships result in regressive income transfers? Do merit-based scholarships increase the probability of course withdrawals? Do these scholarships cause grade inflation in high school? Do they increase enrollment at colleges and universities?

Most of the literature attempting to answer these questions has analyzed data from Georgia's Helping Outstanding Pupils Educationally (HOPE) scholarship. Dynarski (2004) investigated HOPE's effect on an array of educational outcomes in Georgia. She found that HOPE increased

[1] In 2012 the U.S. Department of Education had a discretionary appropriations of $68.1 billion.

[2] These scholarships are distinctly different than need-based scholarship programs that are also prevalent in many states. Merit-based aid is available for any student who meets certain criteria laid out by the state, while need-based aid is for students who qualify based on need, primarily due to guardian's income being below a certain threshold.

[3] These states are Arkansas, Florida, Georgia, Kentucky, Louisiana, Maryland, Michigan, Mississippi, Nevada, New Mexico, South Carolina, Tennessee, West Virginia, Wyoming, and Arizona.

[4] In January of 2012, Louisiana Governor Bobby Jindal said the following when asked about the possibility of capping Louisiana's Taylor Opportunity Program for Students (TOPS) scholarship. "We remain opposed to any efforts to cap TOPS. We think it is an important program that has been very successful."

the probability of college attendance by about five to seven percentage points, and that HOPE was more effective than need-based aid in increasing enrollment. She also found that the scholarship shifted students toward attending four-year schools instead of two-year schools.

Cornwell and Mustard (2007) tested whether the HOPE scholarship allowed wealthier families to substitute money that they would have spent on tuition for a new vehicle. They found a significant increase in the number of vehicle registrations in Georgia after HOPE was implemented, supporting their hypothesis. Cornwell et al. (2005) used enrollment records of undergraduates at the University of Georgia (UGA) to estimate HOPE's effect on course taking. They concluded that HOPE increased course withdrawals among freshmen because students in danger of losing their scholarship were the most likely to withdraw from courses in the first year. The paper also found that HOPE increased the number of summer school credits earned by students. Buglar et al. (1999) studied HOPE's effect on grade inflation in high school but found no evidence that that the implementation of HOPE created or exacerbated grade inflation in Georgia.

Cornwell et al. (2006)–hereafter referred to as CMS–tested HOPE's impact on college enrollment in Georgia. They found that the implementation of HOPE was associated with a 5.9 percent increase in enrollment, translating into almost 2,900 additional students enrolled in Georgia colleges and universities per year. They also found that the rise in enrollment was concentrated in four-year schools, especially private colleges, and that the effect on enrollment was smaller for white students than for other races. Finally, the scholarship led to an increase in the average SAT scores of incoming freshmen at Georgia's public colleges and universities.

While the insights obtained from Georgia are important, it is also valuable to analyze the impacts of similar programs in other states because many of these programs differ substantially from HOPE. This paper tests for the effect of a comprehensive set of outcomes on Arizona's Instrument to Measure Standards (AIMS) scholarship. It is unknown whether AIMS and HOPE have similar effects on many educational outcomes, as these scholarships (1) have different requirements, (2) are implemented in states with very different demographics, (3) were enacted 13 years apart, and

(4) are available for different subsets of schools within their respective states.

HOPE and AIMS have substantially different eligibility requirements. In particular, AIMS' requirements are more stringent than that of HOPE's. Currently, it is unknown how much of an impact scholarship requirements have on a scholarship's effectiveness at increasing enrollment. The specific differences in the eligibility requirements between HOPE and AIMS will be discussed in a Section 1.1.

Another important difference between the HOPE and AIMS programs is the underlying demographics in Georgia and Arizona. For example, according to the 2010 census, Hispanics constitute about 25 percent of Arizona's population, while they only make up about 5 percent of Georgia's population. On the other hand, African Americans make up 28 percent of the population in Georgia, and only 3 percent of the population in Arizona. Merit-based scholarships are potentially more effective with different races, and if these races are more prevalent in different parts of the country, then the scholarships' effectiveness also might be different. While I will not be able to test this hypothesis formally, I will test the enrollment effects of AIMS by race.

A third factor that can have an impact on a scholarship's effectiveness is the time period in which the scholarship is implemented. According to Snyder and Dillow (2011), there were almost 14 million students students enrolled in institutions of higher education in the fall of 1990. By 2009, this number increased to over 20 million, an increase of 48 percent. During this same time period, the inflation-adjusted average tuition at 4-year institutions increased from $12,185 to $20,986.[5] This is an increase of over 72 percent. It is unknown whether the marginal contribution of a scholarship program today is more or less effective in increasing enrollment than it was several decades ago. It might be hypothesized that due to major changes in students' choices to attend college over time, the effectiveness of scholarship programs on students' decisions might also change over time.

[5]These costs include total tuition, room and board rates charged for full-time undergraduate students in degree-granting institutions in 2008-2009 dollars. Source: National Center for Education Statistics Fast Facts.

The final and most notable difference between HOPE and AIMS pertains to the type of colleges at which students can take advantage of the scholarships. HOPE can be used at any eligible public or private college, university or eligible technical college in Georgia. AIMS, on the other hand, is only available to students enrolled at one of Arizona's three publicly funded universities: Arizona State University (ASU), University of Arizona (UA) and Northern Arizona University (NAU). CMS tested HOPE's effects on a wide range of colleges and universities in Georgia. This study focuses primarily on ASU, UA and NAU as the scholarship applies to these institutions only. I also investigate the impact of AIMS on other colleges and universities in Arizona as a falsification test, but I do not expect to find a positive AIMS effect on enrollment at these other institutions because their students are not eligible for the scholarship. There may, however, be a negative effect of AIMS on enrollment at non-covered universities or colleges, as students might substitute away from these institutions to attend ASU, UA, or NAU in order to take advantage of the scholarship.

In this study, I investigate the impact of the AIMS scholarship (the "AIMS Effect") on the number of student applications, number of students admitted, freshmen ACT scores, first-year first-time enrollment (by race and gender), retention rates, and in-state tuition and fees at ASU, UA and NAU. I find AIMS has an impact on both enrollment and tuition. This result is robust when both difference-in-differences (DD) and synthetic control (SC) empirical specifications are employed.

The remainder of Section 1 gives background information on the AIMS and HOPE scholarships. Section 2 describes the empirical specification and data used in this analysis. Section 3 presents the results as well as a variety of robustness checks including a synthetic control model and placebo tests, and Section 4 consists of conclusions and extensions for future research.

1.1 The AIMS Scholarship

Arizona students who graduated from high school in 2006 were the first class eligible for the AIMS scholarship. In order to be eligible, students must meet the following requirements: (a) they must

complete all core high school classes with a grade of B or better, (b) they must have a 3.5 GPA on a 4-point scale in core classes or rank in the top 5% of their class, and (c) they must exceed standards on the three AIMS tests while in high school. Core courses consist of classes such as English, math, and science.[6] The AIMS tests measure student competence in reading, writing, and math. Students who meet these requirements are eligible for an in-state tuition scholarship that is valid for one year. This scholarship can be used at one of Arizona's three large public universities: Arizona State University (ASU), University of Arizona (AU) and Northern Arizona University (NAU). Upon performing adequately in college, the scholarship is renewable for a maximum of four years.[7]

Since the inception of the AIMS scholarship, the number of students who have taken advantage of the scholarship has increased substantially. In 2006, about 1,500 incoming college freshmen took advantage of AIMS. By 2009, this number increased to almost 3,000, an increase of 88 percent. Due to this large increase in the cost of the program as well as current budgetary constraints in Arizona, beginning with the high school graduating class of 2013, the AIMS scholarship will only cover 25 percent of tuition.

The AIMS requirements contrast drastically with Georgia's HOPE scholarship requirements. Georgia students who graduated from high school in 1993 were the first class eligible for the HOPE scholarship. In order to be eligible, students need to graduate from an accredited high school in Georgia with a 3.0 GPA or better. The requirements have remained relatively constant over time.[8] If met, students are eligible for an in-state tuition scholarship that is valid for one year. Similar to AIMS, upon performing adequately in college, the scholarship is renewable for a maximum of four years. Unlike AIMS, though, HOPE can be used at any college or university in Georgia.

[6]There are 16 "core competency" courses that include four units of English, four units of math, three units of Science, two units of social sciences, two units of foreign language, and one unit of art.

[7]Arizona Department of Education 2012.

[8]Some changes have been made to the HOPE scholarship's eligibility requirements. For example, in 1995, the $100,000 parental income cap was removed. Other minor changes have been made over the years.

2 Empirical Strategy

2.1 Empirical Model

2.1.1 Difference-In-Differences (DD) Estimation

Following the empirical strategy employed by CMS to estimate the impact of HOPE on educational outcomes in Georgia, I employ Equation (1) to estimate the impact of AIMS on educational outcomes in Arizona. Control and treatment groups are identified, and the following empirical specification is estimated:

$$\ln(E_{ist}) = \alpha + \delta(S_{AZ} \times A_t) + X'_{st}\zeta + \gamma S_{is} + \beta_t Y_t + \varepsilon_{ist} \tag{1}$$

where E_{ist} is the variable of interest at school i in state s in year t.[9] S_{AZ} is an indicator variable corresponding to the treatment group: Arizona State University (ASU), University of Arizona (UA), and Northern Arizona University (NAU) and is zero for the control schools. A_t is an indicator variable that indicates the post-AIMS time period: 2006 to 2010. X_{st} is a vector of control variables that includes the number of high school graduates, unemployment rate, and average wage observed at the state level. S_{is} represents school fixed effects and Y_t is year fixed effects. The coefficient of interest is δ, as it represents the "AIMS effect."

There are 14 institutions that both ASU and UA consider to be "peer institutions." These peer institutions are Florida State University, University of Illinois at Chicago, University of Illinois at Urbana-Champaign, University of Iowa, University of Maryland-College Park, Michigan State University, University of Minnesota-Twin Cities, Rutgers University-New Brunswick, Ohio State University, University of Texas at Austin, University of Washington-Seattle Campus, and University of Wisconsin-Madison. These will be used as the control group in the differences-in-

[9] Variables of interest include student enrollment, number of applicants, student admissions, ACT scores, retention and tuition.

differences framework.[10]

Year and school level fixed effects are included in all regressions, although these coefficients are not reported. Standard errors are bootstrapped in all regressions.[11]

2.1.2 Synthetic Control (SC) Estimation

There have been substantial critiques to empirical literature that employs DD estimation (Bertrand et al., 2002, 2004; Abadie et al., 2010). Due to critiques primarily about non-robustness to placebo tests especially when the number of treated units is relatively small, researchers have been pushed to conduct additional robustness checks to assure that results from DD estimation are indeed valid. One underlying assumption necessary for DD estimation to be valid is that the treatment group would have been the same as the control group holding all covariates constant post treatment had the treatment not have been implemented. For this reason, choosing an appropriate control group is crucial to validity of this estimation technique. Unfortunately choosing the "right" control group is not always a straight forward or easy process. This is illustrated in this paper, as two of the three universities being analyzed are very similar, ASU and UA, but the third school NAU is less similar. Therefore, the use of SC methods are particularly relevant in this application.

Before creating the synthetic schools, the potential group of control schools is expanded to include all 4-year public universities in the IPEDS southwest region in addition to the control schools

[10]NAU has a very different list of peer institutions due to its difference in size as compared to ASU and UA as is illustrated in Table 1. Instead of trying to pick and choose which institutions are appropriate peers for all three universities, I chose to use just the common peer institutions for ASU and UA. As a robustness check, I ran separate regressions using each school as the sole treatment school. These results of this specification are presented in Table 6 and are discussed further in the results section. Furthermore, similarly ranked institutions in the *U.S. News and World Report College Rankings* were also considered as a potential control group. In 2006, the year when AIMS was implemented, only one of the three schools, University of Arizona, received a ranking and therefore I chose to use the common peers as the control group.

[11]Cluster corrections are not used in calculating the standard errors because the number of schools is not sufficiently large compared to the number of years (17 schools over 10 years). When standard errors are clustered at the institution level, the results do not differ significantly. Not clustering is the more conservative approach, and therefore these more conservative standard errors are reported.

discussed in section 2.1.1.[12] This increases the potential control group from thirteen schools to thirty two schools. Using this expanded group of potential controls, I create a synthetic control control school for ASU, UA and NAU using the methods discussed in Abadie et al. (2010). Then, removing ASU, UA and NAU from the sample, I create synthetic schools for each of the other institutions that will be used to conduct a placebo test.

Following Abadie et al. (2010) synthetic control groups are made by choosing a W^* that minimizes $\sqrt{(X_1 - X_0W)'V(X_1 - X_0W)}$ where X_0 is a vector of pre-intervention characteristics for the exposed regions (or treatment group) and X_1 is a vector of pre-intervention characteristics of the non-exposed regions (or control group). W is a $(J \times 1)$ vector or positive weights that sum to one. V is some $(k \times k)$ symmetric and positive semidefinite matrix. The "synthetic schools" are created by taking a weighted average of the other schools variable of interest. The weights used come from W which was estimated econometrically.

A "synthetic school" is made to correspond with each school in the sample (both control and treatment schools) for purposes of analyzing changes in enrollment by constructing X_0 and X_1 to include the following variables; enrollment, applicants, unemployment rate, total wages, and FHFA HPI.[13] A second "synthetic school" is made to correspond with each school in the sample for purposes of analyzing changes in tuition using the following variables; tuition, high school graduates, unemployment rate, total wages, and FHFA HPI.[14]

Table 1 shows the weights associated with potential control institutions to make up the "synthetic school" for ASU, UA, and NAU for both enrollment and tuition. As can be expected, the weighting vector used to create the synthetic schools for ASU and UA enrollment are very similar, thus speaking to the validity of using the same control group in the DD estimation. As is also expected, the synthetic control school for NAU is quite different, thus reaffirming the need for

[12]The IPEDS southwest region includes Arizona New Mexico, Oklahoma and Texas. No other schools within Arizona are included in the expanded control group as they were potentially impacted by AIMS.

[13]The natural log of each one of these variables is used to be consistent with regression results.

[14]The natural log of these variables is also used to be consistent with regression results.

conducting SC estimation. Importantly, the SC methods are consistent with colloquial knowledge of these institutions. Figure 1 also shows that the synthetic control group used for estimating the AIMS effect on tuition is almost identical for these three schools. This is expected, as the same board of regents approves tuition increases for all three of these schools, and therefore the tuition increases at these three institutions is very consistent across the different institutions.

2.2 Data

I use data from the Integrated Post Secondary Education Data System (IPEDS) published by the National Center for Education Statistics (NCES) as the sole source of dependent variables. IPEDS has yearly data on over 7,400 colleges and universities throughout the United States. Independent variables used in this paper include (a) first-year first-time enrollment of freshman (by race and gender), (b) number of applicants, (c) student admissions, (d) ACT scores of entering freshman[15], (e) retention rates, and (f) in-state tuition and fees.[16]

Three control variables are employed. The first is the number of high school graduates by state from the National Center for Education Statistics (NCES).[17] It is hypothesized that as the number of high school graduates increases in a state, so too will the enrollment at that state's colleges and universities. Previous research has shown that economic conditions can affect students' decision to drop out of high school (Rees and Mocan, 1997), whether to attend/continue college (Mincer, 1974; Dellas and Sakellaris, 2003; Dellas and Koubi, 2003), and potentially students' choice of major (Lee, 2010).[18] Therefore, two additional variables are employed to control for labor mar-

[15]IPEDS does not provide average ACT scores, but instead provides the 25th and 75th percentile of ACT scores of incoming freshmen. This paper utilizes the average of these two.

[16]Ideally, I would have limited the analysis to only in-state students, but due to data availability, this is not possible. CMS were subject to the same data limitations, and therefore they also used all first-time freshmen as their independent variable of interest.

[17]The estimated 18-24 year old population by state from the U.S. Census Bureau was also used, but because these two variables are highly collinear, they were used interchangeably as a robustness check. The results were robust to both variables, and therefore only regressions with high school graduates will be reported.

[18]Mincer discuss the human-capital investment-model which includes cyclic labor market conditions as a potential reason to not obtain additional schooling.

ket conditions. These variables are the unemployment rate obtained from the Bureau of Labor Statistics' Local Area Unemployment Statistics (LAUS) and the average weekly wage from Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW).[19] Lovenheim and Reynolds (2013) and Lovenheim (2011) test the impact of housing wealth on college choices and find that increases in housing wealth can lead to an increase in college enrollment. Therefore the state-level housing price index published by the Federal Housing Finance Agency (FHFA) is also used as a covariate.[20] The data set contains state-level information on each of these variables from 2000 to 2010.

Table 2 presents the change in two key variables: enrollment and tuition at the three universities analyzed in this study (ASU, UA, and NAU) between 2005 (the year before AIMS was implemented) and 2010 (the most recent year in the sample). First-year first-time enrollment of freshman increased at all three universities over the course of this time period, with NAU's increase of 80 percent being the most notable. ASU's and UA's enrollment increased by about 12 and 18 percent respectively. While NAU experienced the largest percent increase in enrollment, it also has the smallest first-year first-time enrollment both before and after the implementation of AIMS.

Equally as noticeable as the change in enrollment is the change in tuition. Tuition increased by over 74 percent at all three institutions, with the highest increase (84.6 percent) at ASU. While these increases appear large, both tuition and enrollment are on the upward trend nation-wide as previously discussed. Figure 1 presents a graphical representation of the increase in both enrollment and in-state tuition and fees for the treatment and control groups. The increase in enrollment of the treatment group compared to the control group is particularly apparent after the implementation of AIMS in 2006.

Table 3 presents the description of the variables as well as their summary statistics. All of the

[19]NAICS 23 Construction and NAICS 31-33 Manufacturing were also used to proxy for low skilled labor that is potentially available for high school graduates. When these variables are used in the place of total average weekly wages, the results are similar, and therefore regressions with the inclusion of these industry specific variables are not included in the results

[20]Specifically, the average monthly seasonally adjusted housing price index by year is used.

universities in the sample are quite large, with an average of over 21,000 applicants and 13,000 students admitted per year. The first-year first-time incoming freshmen classes average over 5,000 students per year and the average in-state student pays about $6,500 in tuition and fees each year. Retention rates are 85 percent on average.

3 Results

Table 4 presents the estimated impact of AIMS on the number of applicants at ASU, UA, and NAU. The estimated AIMS effect on the number of applicants is quite large, about 20 percent for both men and women, although it is not statistically significantly different than zero. This increase in applicants after the implementation of AIMS can also be seen graphically in Figure 2, which shows an increase in the average number of applicants in the treatment group compared to the control group after the implementation of AIMS in 2006. While the estimated impact is large, due to the lack of statistical significance, I do not have sufficient evidence to conclude that AIMS increased the number of applicants at these universities. This result can be explained if students "cast a wide net" when applying for colleges, and therefore apply in either the presence or absence of AIMS.

Table 5 presents the findings on the number of students who are admitted each year to ASU, UA, and NAU. These results serve two purposes. First, this tests whether more students were admitted after the implementation of AIMS. Secondly, it provides insight to whether the schools themselves changed their admissions policies due to the scholarship. As seen in Table 4, when the number of applicants is not controlled for, the estimated magnitude of the AIMS effect on student admissions is quite large, about 12 to 13 percent (although not statistically significant), but when the number of applicants is controlled for, the estimated AIMS effect attenuates and actually becomes slightly negative, but is still statistically insignificant. Figure 2 illustrates this increase in admissions in the treatment group compared to the control group at these universities after 2006.

Again, though, due to the statistical insignificance of this effect, I do not have sufficient evidence to conclude that more students were admitted due to the scholarship. Equally as important, I find no evidence that the schools have changed their admittance decisions due to the scholarship, as the number of students admitted, holding applicants constant, also did not change.

Table 6 presents the estimated enrollment effects and shows a statistically significant overall AIMS effect as well as an impact for both men and women separately. A 15 percent increase in overall first-year first-time enrollment–hereafter simply referred to as "enrollment"–is estimated using this framework. The AIMS effect is estimated to be higher for women than for men, about 16-17 percent for women as compared to 14 percent for men. These results are robust when the unemployment rate, wages, and housing prices are used as covariates. I find no impact of either the unemployment rate or average weekly wages on enrollment. Because no AIMS effect was observed on either applicants or admissions, this increase in enrollment is most likely attributable to students' choices of where to attend college.

At first glance, this estimated increase in enrollment appears large compared to CMS who estimated a 5.9 percent increase in Georgia enrollment due to the HOPE scholarship. But upon further consideration, it is not at all surprising as the HOPE scholarship is available to students who attend any public college or university in Georgia, while AIMS is only available to three in-state institutions. Therefore, it is not surprising that these institutions see a relatively large percentage increase in enrollment compared to the overall percentage increase that all colleges and universities in Georgia received.

Next, Table 7 presents estimates of the AIMS effect on enrollment for each university separately. The enrollment effects for ASU and UA are roughly the same, between 10 and 11 percent. The enrollment effect for NAU is much larger: about 24-25 percent. While the percent increase in enrollment for NAU is much larger, NAU is a much smaller school and therefore the actual increase in the number of students is not necessarily larger. For instance, in 2005, the year before AIMS was implemented, NAU enrolled 2,105 students, while ASU and UA enrolled 7,396 and

5,785 students respectively. Therefore, while the percent increases for NAU is larger, the actual magnitude of the increase in number of students is similar. This estimated increase in the number of students enrolled is discussed in detail in Section 3.1.

As presented in Table 1, ASU experienced a 11.7 percent increase in enrollment from 2005 to 2010, and Table 6 presents the estimated AIMS effect on enrollment at ASU to be approximately 11 percent. UA and NAU, on the other hand, experienced an approximately 18 and 80 percent increase in enrollment respectively over this same time period, but the estimated impact of AIMS on enrollment is about 11 and 25 percent respectively. According to these results, almost all of the increase in enrollment seen at ASU after the implementation of AIMS can be attributed to the AIMS scholarship, while only 61 and 31 percent respectively of the increases in enrollment at UA and NAU can be associated with AIMS. Less formally, enrollment would have increased at UA and NAU regardless of whether AIMS was implemented, but enrollment increased more than it otherwise would have due to the implementation of AIMS.

In Tables 8-10, I present estimates of the the AIMS effect on enrollment for white, black, and Hispanic students separately. The average enrollment over time for each of these races in both the treatment and control group is presented in Figure 4. White enrollment appears to increase after the implementation of AIMS compared to the control group, but this increase is relatively small when compared with the increase in Hispanic enrollment, for example, which shows a relatively large increase in enrollment post AIMS. There is no noticeable change in Asian or American Indian enrollment after the implementation of AIMS compared to the treatment group. Black enrollment was already trending upwards before the implementation of AIMS compared to the control group, but this trend is exacerbated after 2006. Next, I present the empirical results for whether these increases are statistically significant after controlling for relevant covariates.

Table 8 presents a statistically significant impact of AIMS on enrollment for white students; approximately a 6 to 8 percent increase. The estimated AIMS effect is similar larger for women than for men and the estimated enrollment effect is not statistically significant for men. Notice as

well that the estimated AIMS effect on white students is significantly lower than the overall AIMS effect presented in Table 6. This indicates that the AIMS effect is likely larger for minorities. This result is consistent with CMS's findings on the impact of HOPE on enrollment in Georgia. Table 8 presents coefficient estimates for enrollment effects on black students. These point estimates are much larger than the estimated AIMS effect for white students. Overall AIMS has increased enrollment of black students by about 25 percent. The estimated AIMS effect on enrollment for black men is 32 percent, higher than for any other group. While the AIMS effect was estimated to be slightly larger for white women than for white men, the converse is observed with black women and men as the estimated AIMS effect for black men is about 13 percentage points larger than for black women.

Table 10 shows the estimated AIMS effect on Hispanic enrollment. These point estimates are on average larger than the overall estimated AIMS effects, but not as large in magnitude as the coefficients estimating black enrollment effects. Specifically, a 21 to 23 percent enrollment effect is estimated. The estimated effect is similar for Hispanic men and women. Again these results are robust to the inclusion of covariates that control for economic conditions. Figure 4 shows a graphical representation of the enrollment effects by race presented in Tables 8-10.[21]

The AIMS scholarship can only be used at one of the three schools being analyzed in the previous regressions, ASU, UA, and NAU. For this reason, it is not surprising that AIMS had an impact on enrollment at these schools, but it is unknown what these new enrollees would have done had they not attended one of these three universities. First, these students may not have attended college at all if AIMS was not available. Because AIMS has very stringent requirements (a 3.5 high school GPA as well as a passing score on three exams) it seems unlikely that these students would not attend college in the absence of AIMS. A second possibility is that these students are substituting away from other schools in Arizona to attend ASU, UA, or NAU due to the scholarship.

[21]Results for the AIMS effect on American Indian and Asian student enrollment is also available upon request. These results are not statistically significant and are therefore regression tables are not included. Graphical representations are included in Figure 4.

Third, the students may substitute away from out-of-state colleges and universities and instead choose to stay in state. I explore these three possibilities.

First, I test whether students are substituting away from other in-state schools to attend ASU, UA, and NAU. Table 12 presents the estimated enrollment effects of AIMS at other colleges and universities in Arizona. Specifically, in these regressions the treatment group contains all Arizona schools except ASU, UA and, NAU, and the control group contains all schools in in New Mexico, Texas, and Oklahoma. I estimate separate regressions for (a) all colleges and universities in Arizona, (b) all four-year (public and private) colleges and universities, as well as (c) two-year institutions. The results presented in Table 12 serve two purposes. First, they test to see if AIMS had a negative impact on enrollment at other institutions in the state. If a negative relationship is found, then it provides evidence that students are substituting away from other schools in Arizona. It also serves as a falsification test for previous results. Because AIMS is not available to students who attend these other in-state schools, if a positive significant AIMS effect on enrollment is found, this will be a warning that previous results are potentially problematic. As can be seen in Table 11, no AIMS effect is observed on enrollment at any institution and therefore the substitution hypothesis is not supported.[22]

Due to the lack of evidence that students are substituting away from other colleges and universities in Arizona to attend either ASU, UA, or NAU, I explore the other two possible explanations for these new students. First, these new students may otherwise not attend college if AIMS were not available. Second, students might attend schools out of state if not for AIMS. While I cannot directly test which of these effects dominates, I can test whether the quality of students at ASU, UA and NAU changed due to the AIMS scholarship using two different measures: incoming freshmen American College Testing (ACT) scores and retention rates. Students who are on the margin of

[22]Separate analysis was conducted analyzing the impact of the AIMS scholarship on Maricopa Community College system's enrollment. Maricopa Community College has seven separate schools located near Phoenix Arizona. I find no impact of AIMS on these colleges, and therefore I find no evidence to support the hypothesis that students are substituting away from these local community colleges to attend ASU, UA or NAU. These results are available upon request.

whether to attend college may have lower credentials, such as ACT scores, upon entering college and will potentially be more likely to drop out. If the quality of students does not change or increases due to AIMS, then it is unlikely that these new students were on the margin of whether to attend college.

Table 12 tests for the impact of AIMS on ACT scores.[23] I find a decrease in composite ACT test scores by less than 1 point (.768 points). While this result is statistically significant, it is not economically significant, as the ACT has a maximum score of 36 points, with a mean of 18 and standard deviation of 6. Therefore, I estimate a decrease of less than 15 percent of one standard deviation. Furthermore, when separate regressions are run on English or math scores, no statistically significant impact is found. Therefore, the quality of incoming freshmen as measured by ACT scores has not declined. One potential explanation for the very slight drop in ACT scores might have to do with the AIMS scholarship itself. Because AIMS does not require students perform well on the ACT, but rather the three AIMS exams in high school, students may substitute studying away from the ACT toward the AIMS exams. This result contrasts with CMS, who found that HOPE led to an increase in SAT scores.[24]

Table 13 also tests for quality of student by estimating AIMS' impact on retention rates. Retention rates are the proportion of students enrolled in one semester that are still enrolled the next semester, excluding students who graduate. These regressions estimate that AIMS increased retention rates by less than 2 percent, but these are not statistically significant at any level.[25] Therefore, there is no evidence to conclude that AIMS had a negative impact on retention rates at ASU, UA and NAU. These results are robust when economic conditions are controlled for. Figure 4 shows a

[23]University of Maryland –College Park and University of Connecticut are excluded from these regressions as applicants at these schools primarily take the SAT, unlike the other schools in the sample who are primarily interested in ACT scores.

[24]The SAT test is similar to the ACT test in that it is a standardized test that is taken before applying to college. SAT was previously an acronym for "Scholastic Assessment Test" but is now an empty acronym.

[25]It should be noted that data is not available on retention rates of just first year students, therefore this is not a perfect measure of retention of students exposed to AIMS.

graphical representation of the change in quality of students over time as measured by ACT scores and retention rates. Because I find no evidence that the quality of students at these universities decreased after the implementation of AIMS and no evidence that students are substituting away from other in-state colleges, the most likely explanation is that students are substituting away from out of state colleges to stay in Arizona.[26]

Finally, Table 14 presents estimates of the AIMS effect on in-state tuition and fees. I find a statistically significant and large impact of a 16 to 20 percent increase in tuition and fees due to the AIMS scholarship. Table 1 shows a much larger change in tuition from 2005 to 2010, about a 75 to 85 percent increase. These results suggest that there would have been an increase in tuition regardless of whether AIMS was implemented. However, tuition increased more than it otherwise would have due to AIMS. This result is intuitive. Because some students' education is heavily subsidized, the aggregate price sensitivity is reduced. Therefore, universities have greater liberty to increase tuition without compromising enrollment.

Next, the main result of the paper is replicated using SC methods. In particular, the overall AIMS effect on enrollment and tuition is estimated. The difference between the synthetic schools' enrollment and actual enrollment as well as the difference between the synthetic schools' tuition and actual tuition is presented in Figure 5. As can be seen, the difference between the treated schools and their respective synthetic schools increases after AIMS was implemented. Furthermore, the difference between the other controls and their synthetic schools does not change before and after the treatment.

Figure 6 illustrates these results further by showing a histogram of the estimated treatment effect using just each school and its synthetic control. Equations 2 and 3 illustrate the DD estimation technique used to estimate the AIMS effect on enrollment and tuition where there is only one treatment school and one control school (the synthetic control). Each school in the sample is "treated"

[26]Retention rates are for all students, not just students who drop out after their first year. For this reason, this is an imperfect measure of retention rates of the impacted studentss.

and compared to its synthetic school. If the previous results in this paper are robust, then δ will be approximately zero for the non-Arizona schools and δ will be similar to the point estimates presented in Tables 7 and 14 for the Arizona schools.

$$ln(E_{ist}) = \alpha + \delta(S_T \times A_t) + \gamma S_{is} + \beta_t Y_t + \varepsilon_{ist} \tag{2}$$

$$ln(T_{ist}) = \alpha + \delta(S_T \times A_t) + \gamma S_{is} + \beta_t Y_t + \varepsilon_{ist} \tag{3}$$

The estimated AIMS Effect on Enrollment for ASU, UA and NAU using this synthetic control group is 16.8%, 14.9% and 26.83% respectively. Notice, these estimates are actually slightly larger than the results presented in Table 7, thus giving evidence that if anything, DD results are downward biased. The estimated AIMS effect on tuition and fees using the SC group for ASU, UA and NAU are 21.2%, 20.9% and 18.5% respectively. These results are similar to the estimated AIMS effect of 16-19.5% presented in Table 14.

Next, I implement a placebo test by estimating the AIMS effect for every other school in the sample relative to its synthetic school. Figure 6 illustrates that the estimated AIMS effect on both enrollment and tuition are large compared to the estimated effects for the other schools that were used as a placebo test. In fact, all of the other schools' estimated AIMS effects are centered around zero. The estimated AIMS effects on tuition for ASU, UA and NAU are three of the top four and the estimated AIMS effect on tuition of ASU, UA and NUA are the three highest. This speaks to the robustness of these results to SC methods and placebo tests.

3.1 Percent of Scholarship Dollars Spent on Marginal Students

I have shown that AIMS has led to an increase in first-year first-time freshmen enrollment at ASU, UA, and NAU. In this section, I consider the following question: What percent of the scholarship recipients would not have attended one of the three treatment schools if they were not eligible for AIMS? Conversely, what percent of the students who receive AIMS would attend one of these

three schools even if they were not eligible for AIMS (i.e., their college decision is not altered by the scholarship)? I consider the following:

$$E_i^a = (1 + \hat{\delta}_{i,1})E_i^c \tag{4}$$

Where E_i^a is the actual number of students who were enrolled in school i in 2010 and E_i^c is the "counterfactual" number of students school i, or the number of students who would be enrolled if AIMS were not implemented. Solving for $E_i^a - E_i^c$, I get the following

$$E_i^a - E_i^c = E_i^a\left(\frac{\hat{\delta}_{i,1}}{1 + \hat{\delta}_{i,1}}\right) \tag{5}$$

This equation provides the estimated difference in the number of students who actually attended one of the treatment schools that would not have attended if AIMS were not available. Table 1 shows the actual 2010 enrollment at each of these three schools. Table 6 shows two estimates of $\hat{\delta}_{i,1}$ for each school. For these calculations, I will use the estimated coefficients in regressions (2), (4), and (6) as they include the full list of covariates. Using these inputs into Equation 5, I find that enrollment increased by 825, 663, and 748 students at ASU, UA, and NAU respectively.[27]

These are the estimated number of students who attended ASU, UA and NAU that would not have otherwise done so without AIMS. I do not know the number of students who actually received the scholarship at each of these schools, but I do know that 2,935 students in total utilized the scholarship in 2009.[28] Summing the additional students from (4)-(6) yields 2,217 students. Therefore, I estimate that 718 of the 2,935 students, or 24 percent, who received the scholarship in 2009 would have attended one of these schools regardless of whether they were eligible for AIMS. Therefore, conversely, 76 percent of the students who received the AIMS scholarship would not

[27] $E_{ASU}^a - E_{ASU}^c = 8,261\left(\frac{.111}{1+.111}\right) = 825$ Students, $E_{UA}^a - E_{UA}^c = 6,804\left(\frac{.108}{1+.108}\right) = 663$ Students, $E_{NAU}^a - E_{NAU}^c = 3,789\left(\frac{.246}{1+.246}\right) = 748$ Students

[28] This data has not been released for 2010.

have attended either ASU, UA, or NAU if the scholarship were not available. They would have either (a) not attended college at all (b) attended a school out of Arizona or (c) attended another school in state. I am unable to empirically examine the magnitude of each of these alternatives, but as discussed previously, it appears that (b) is the most likely explanation for these additional students.

Using these calculations, I can also obtain a rough estimate of the dollar value of the transfer to students who would attend ASU, UA, or NAU regardless of whether the scholarship was available. Multiplying a simple weighted average of tuition in 2010 from Table 1 ($8,788) by the 718 students who would have attended one of these universities regardless of whether the scholarship was available, yields an estimated $5.8 million subsidy to incoming freshmen that did not affect enrollment decisions.

4 Conclusions

This paper finds strong evidence of an AIMS effect on enrollment at Arizona's three large in state universities, Arizona State University (ASU), University of Arizona (UA) and Northern Arizona University (NAU). These enrollment effects are strongest for black and Hispanic students. I do not find evidence that AIMS impacts the quality of students at these universities as measured by ACT scores of incoming freshmen and retention rates. I do, however, find that AIMS led to an increase in tuition and fees. Results obtained from DD estimation as well as SC groups are consistent. Furthermore, the specification is robust to placebo tests using SC methods.

While these results are quite consistent with CMS's analysis of the HOPE scholarship, there are several differences between AIMS and HOPE that can provide insight about state wide merit-based scholarships. First, the scholarships were implemented in different time periods. HOPE was implemented in 1993 while AIMS began in 2006. Because a growing number of students are attending college every year, the marginal contribution of any program aimed at increasing

enrollment might be hypothesized to be lower today than it was in 1993. Therefore, analyzing a scholarship that was implemented in 1993 might not be relevant for a policy maker wanting to create or change a policy today. My research shows that AIMS was effective at increasing enrollment in 2006.

The second obvious difference between the programs is the geographic region of the country where the scholarships were implemented. If these programs are more effective for a particular demographic of students, and that demographic is more common in Georgia than Arizona, for instance, then this might explain the difference in outcomes. In particular, I find that the scholarship is most effective among black and Hispanic students. Given these results, it is not surprising that both AIMS and HOPE were effective in their respective states whose populations are comprised of a large percent of Hispanics and blacks respectively.

Finally, it is possible that the requirements of a scholarship might have an impact on the effectiveness of these scholarship. In particular, the AIMS scholarship has much more strict requirements than does HOPE, but nonetheless the program was still effective at increasing enrollment. It must be noted that Georgia's HOPE scholarship can be used at any approved school in Georgia, while AIMS is restricted only to Arizona's three largest state schools (ASU, UA, and NAU). It is unknown whether AIMS would have had an impact on enrollment at other schools in Arizona if it were available.

While we have learned a great deal about merit-based scholarship programs, there are still many questions that have not been answered. First, I have estimated that merit-based scholarship programs can lead to an increase in tuition. This increase in tuition, though can have a negative impact on enrollment (Berger & Kosta 2002, Dellas & Sakellaris 2003). This paper is only able to test for the net of the increase in enrollment due to the scholarship's availability to some students and the decrease in enrollment associated with the increase in tuition. Future research might be interested in testing for each effect separately.[29]

[29]It is possible to use tuition as a control variable in the estimation of the AIMS effect on en-

While similar, the effects of HOPE and AIMS on many of the variables of interest are not identical. I am only able to hypothesize on why these differences exist. Future research might be interested in the relationship between enrollment effects of a scholarship and the minimum requirements necessary to be eligible for the scholarship, for instance. It can be hypothesized that more stringent scholarships will have smaller impacts on enrollment, but the difference in magnitudes of these effects are unknown. This research will be useful to policy makers when constructing or changing scholarships.

Future research might also be interested in whether scholarships have become less effective as time has progressed. This might be the case if less students today are "on the margin" of whether or not to attend college. If this is the case, then a scholarship program might have a smaller effect today than it did when HOPE was implemented. While this paper shows that AIMS was effective at increasing enrollment, it is unknown how much of an impact the program would have had on enrollment if it were implemented a decade earlier.

The possibilities for future research on state merit-based scholarship programs are vast, and a better understanding of these programs will allow policy makers to design programs that maximize outcomes of interest while minimizing the overall cost of the program. This research will add to the understanding of the AIMS scholarship in particular as well as to the broader literature on scholarship programs.

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rollment, but the inclusion of this variable will create an endogeneity problem, as tuition and enrollment are jointly determined by both the supply and demand for college. For this reason, tuition was not used as a control variable in these regressions.

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Tables and Figures

Table 1: Synthetic Control Group Weights

	ASU	UA	NAU
Enrollment			
Florida State University	57.1%	57.2%	-
Michigan State University	26.3%	30.3%	-
University of Minnesota-Twin Cities	11.2%	8.2%	21.1%
University of New Mexico-Main Campus	4.2%	-	-
University of Washington-Seattle Campus	-	-	21.8%
University of Wisconsin Colleges	-	-	47.4%
Tuition			
Michigan State University	16.5%	16.5%	16.5%
University of Minnesota-Twin Cities	32.9%	32.9%	32.8%
University of New Mexico-Main Campus	10%%	10.1%	10.1%
New Mexico State University-Main Campus	10%%	10%	10.1%
University of Wisconsin Colleges	30.5%%	30.5%	30.5%

Table 2: Change in Enrollment and Tuition Over Time

	2005	2010	% Change
Arizona State University (ASU)			
Enrollment	7,396	8,261	11.7%
Tuition	$4,406	$8,132	84.6%
University of Arizona (UA)			
Enrollment	5,785	6,804	17.6%
Tuition	$4,498	$8,237	83.1%
Northern Arizona University (NAU)			
Enrollment	2,105	3,789	80.0%
Tuition	$4,393	$7,672	74.6%

Full-time first-time degree/certificate-seeking undergraduate students

Table 3: Summary Statistics and Variable Descriptions

Variable	Description	Mean	SD	N
Total Applicants	FTFY degree-seeking applicants total	21,508	9,055	170
Male Applicants	FTFY degree-seeking applicants - Men	10,062	4,252	170
Female Applicants	FTFY degree-seeking applicants - Women	11,444	4,913	170
Total Admissions	FTFY degree-seeking admissions total	12,960	4,003	170
Male Admissions	FTFY degree-seeking men admitted	5,899	1,940	170
Female Admissions	FTFY degree-seeking women admitted	7,060	2,159	170
Enrollment Total	FTFY degree-seeking enrolled full time total	5,162	1,540	170
Enrollment Men	FTFY degree-seeking men enrolled full-time	2,421	785	170
Enrollment Women	FTFY degree-seeking women enrolled full-time	2,740	798	170
ACT Total	Average of ACT Composite 25th and 75th percentile score	24.7	2.1	138
ACT English	Average of ACT English 25th and 75th percentile score	24.3	2.4	120
ACT Math	Average of ACT Math 25th and 75th percentile score	24.8	2.5	120
Tuition	Published in-state tuition and fees	$6,533	$2,628	187
Retention Rate	Full-time retention rate	85%	9.9%	115
Unemployment Rate	Statewide-Not Seasonally Adjusted	6.1%	2.1%	170
High School Graduates	Total High School Graduates	104,282	80,681	186
FHFA Index	Federal Housing Finance Agency Housing Price Index	216.8	41.04	170

"FYFT" stands for "First-Year First-Time"

Table 4: Estimated AIMS Effect on the Number of Applicants by Gender

	(1) All	(2) All	(3) Men	(4) Men	(5) Women	(6) Women
AIMS Effect	0.205	0.202	0.208	0.207	0.200	0.196
	(0.190)	(0.220)	(0.172)	(0.172)	(0.218)	(0.206)
Ln(H.S. Grad)	-0.215	-0.216	-0.201	-0.202	-0.227	-0.227
	(0.452)	(0.439)	(0.383)	(0.280)	(0.442)	(0.415)
Ln(Unemp)		-0.00871		-0.00418		-0.0136
		(0.184)		(0.193)		(0.232)
Ln(Total Wages)		2.075*		1.828**		2.302*
		(1.087)		(0.781)		(1.254)
Ln(FHFA HPI Index)		-0.332		-0.313		-0.354
		(0.203)		(0.248)		(0.251)
Observations	169	169	169	169	169	169
R^2	0.550	0.576	0.580	0.603	0.516	0.546

Bootstrapped standard errors are reported in parentheses. School and year fixed effects are included in all regressions. Treatment Group includes UA, ASU and NAU. Control Group includes peer institutions.

Table 5: Estimated AIMS Effect on the Number of Students Admitted by Gender

	(1) All	(2) All	(3) Men	(4) Men	(5) Women	(6) Women
AIMS Effect	0.128	-0.0356	0.134	-0.0330	0.123	-0.0361
	(0.0956)	(0.141)	(0.0841)	(0.134)	(0.0864)	(0.137)
Ln(Total Applicants)		0.800***				
		(0.257)				
Ln(Men Applicants)				0.801***		
				(0.259)		
Ln(Women Applicants)						0.799***
						(0.217)
Ln(H.S. Grad)	0.195	0.367	0.194	0.355	0.190	0.371
	(0.292)	(0.350)	(0.298)	(0.335)	(0.256)	(0.344)
Observations	169	169	169	169	169	169

Bootstrapped standard errors are reported in parentheses. School and year fixed effects are included in all regressions. Treatment Group includes UA, ASU and NAU. Control Group includes peer institutions.

Table 6: Estimated AIMS Effect on Enrollment of First-Year First-Time Degree Seeking Freshmen

	(1) All	(2) All	(3) Men	(4) Men	(5) Women	(6) Women
AIMS Effect	0.150***	0.152***	0.139***	0.139***	0.165***	0.170***
	(0.0416)	(0.0581)	(0.0506)	(0.0523)	(0.0470)	(0.0568)
Ln(H.S. Grad)	0.120	0.126	0.148	0.162	0.0916	0.0902
	(0.125)	(0.118)	(0.169)	(0.156)	(0.153)	(0.146)
Ln(Unemp)		-0.0242		-0.0635		0.00997
		(0.114)		(0.182)		(0.0749)
Ln(Total Wages)		0.571		0.334		0.767
		(0.467)		(0.628)		(0.536)
Ln(FHFA HPI Index)		-0.137*		-0.0888		-0.190*
		(0.0799)		(0.144)		(0.111)
Observations	169	169	169	169	169	169
R^2	0.391	0.407	0.413	0.417	0.299	0.337

Bootstrapped standard errors are reported in parentheses. School and year fixed effects are included in all regressions. Treatment Group includes UA, ASU and NAU. Control Group includes peer institutions.

Table 7: Estimated AIMS Effect on the number of First Year First Time Degree Seeking Freshmen By School

	(1) ASU	(2) ASU	(3) UA	(4) UA	(5) NAU	(6) NAU
AIMS Effect	0.113***	0.111***	0.108***	0.107***	0.246***	0.247***
	(0.0217)	(0.0312)	(0.0267)	(0.0240)	(0.0247)	(0.0285)
Ln(H.S. Grad)	0.118	0.135	0.0175	0.0424	0.0756	0.0955
	(0.141)	(0.159)	(0.127)	(0.131)	(0.146)	(0.163)
Ln(Unemp)		-0.0224		-0.0519		-0.0131
		(0.133)		(0.112)		(0.125)
Ln(Total Wages)		0.471		0.309		0.569
		(0.391)		(0.548)		(0.495)
Ln(FHFA HPI Index)		-0.0810		-0.0727		-0.144
		(0.0886)		(0.0943)		(0.0923)
Observations	149	149	149	149	149	149
R^2	0.281	0.292	0.284	0.292	0.374	0.394

Bootstrapped standard errors are reported in parentheses. School and year fixed effects are included in all regressions. Treatment Group includes UA, ASU and NAU. Control Group includes peer institutions.

Table 8: Estimated AIMS Effect on First Year First Time Enrollment of White Students

	(1) All	(2) All	(3) Men	(4) Men	(5) Women	(6) Women
AIMS Effect	0.0661**	0.0710**	0.0619	0.0586	0.0733**	0.0867**
	(0.0283)	(0.0313)	(0.0394)	(0.0418)	(0.0336)	(0.0370)
Ln(H.S. Grad)	-0.134	-0.109	-0.0739	-0.0798	-0.207	-0.151
	(0.150)	(0.146)	(0.176)	(0.167)	(0.178)	(0.150)
Ln(Unemp)		-0.100		-0.0431		-0.162
		(0.198)		(0.212)		(0.143)
Ln(Total Wages)		-0.345		-0.552		-0.153
		(0.535)		(0.504)		(0.694)
Ln(FHFA HPI Index)		-0.0484		0.0792		-0.179
		(0.172)		(0.154)		(0.141)
Observations	143	143	143	143	143	143
R^2	0.036	0.051	0.075	0.093	0.064	0.098

Bootstrapped standard errors are reported in parentheses. School and year fixed effects are included in all regressions. Treatment Group includes UA, ASU and NAU. Control Group includes peer institutions.

Table 9: Estimated AIMS Effect on First Year First Time Enrollment of Black Students

	(1) All	(2) All	(3) Men	(4) Men	(5) Women	(6) Women
AIMS Effect	0.252***	0.250**	0.322***	0.321**	0.196**	0.193**
	(0.0954)	(0.121)	(0.116)	(0.142)	(0.0811)	(0.0789)
Ln(H.S. Grad)	-0.267	-0.162	-0.350	-0.303	-0.177	-0.0257
	(0.432)	(0.574)	(0.382)	(0.615)	(0.559)	(0.635)
Ln(Unemp)		-0.396**		-0.146		-0.593**
		(0.190)		(0.175)		(0.256)
Ln(Total Wages)		2.138		1.406		2.576
		(1.668)		(1.936)		(1.805)
Ln(FHFA HPI Index)		-0.420		-0.224		-0.565*
		(0.299)		(0.313)		(0.332)
Observations	143	143	143	143	143	143
R^2	0.201	0.249	0.218	0.229	0.167	0.245

Bootstrapped standard errors are reported in parentheses. School and year fixed effects are included in all regressions. Treatment Group includes UA, ASU and NAU. Control Group includes peer institutions.

Table 10: Estimated AIMS Effect on First Year First Time Enrollment of Hispanic Students

	(1) All	(2) All	(3) Men	(4) Men	(5) Women	(6) Women
AIMS Effect	0.235***	0.211***	0.241***	0.211***	0.231***	0.211***
	(0.0349)	(0.0365)	(0.0636)	(0.0642)	(0.0324)	(0.0294)
Ln(H.S. Grad)	-0.299	-0.269	-0.548	-0.546	-0.0926	-0.0372
	(0.382)	(0.299)	(0.398)	(0.334)	(0.310)	(0.312)
Ln(Unemp)		-0.317*		-0.214		-0.411**
		(0.170)		(0.173)		(0.169)
Ln(Total Wages)		0.952		1.200		0.814
		(1.290)		(2.282)		(1.205)
Ln(FHFA HPI Index)		-0.0373		0.0325		-0.103
		(0.0987)		(0.136)		(0.164)
Observations	143	143	143	143	143	143
R^2	0.616	0.653	0.583	0.609	0.518	0.562

Bootstrapped standard errors are reported in parentheses. School and year fixed effects are included in all regressions. Treatment Group includes UA, ASU and NAU. Control Group includes peer institutions.

Table 11: Enrollment Effects of AIMS at Arizona Colleges and Universities

	(1) All	(2) All	(3) 4 Year	(4) 4 Year	(5) 2 Year	(6) 2 Year
AIMS Effect	0.145	0.0804	0.189	0.122	0.248	0.136
	(0.218)	(0.186)	(0.216)	(0.187)	(0.200)	(0.193)
Ln(H.S. Grad)	0.404	0.280	0.408	0.139	0.325	0.156
	(0.302)	(0.361)	(0.345)	(0.367)	(0.483)	(0.410)
Ln(Unemp)		0.275		0.260		0.503
		(0.237)		(0.243)		(0.380)
$\text{ltotal}_w ages$		-1.023		-2.005		-1.356
		(1.385)		(1.423)		(2.833)
Ln(FHFA HPI Index)		0.284		0.341		0.460
		(0.300)		(0.297)		(0.401)
Observations	1010	1010	890	890	540	540
R^2	0.028	0.030	0.053	0.057	0.053	0.057

Bootstrapped standard errors are reported. School and year fixed effects are included in all regressions. Treatment group includes colleges and universities in Arizona. Control group includes collegs and universities in NM, TX, and OK. ASU, UA, and NAU are not included in any of these regressions.

Table 12: Estimated AIMS Effect on the Average ACT Score of Incoming Freshmen

	(1) Composite	(2) English	(3) Math
AIMS Effect	-0.768**	-0.229	-0.462
	(0.356)	(0.355)	(0.589)
Ln(Unemp)	-0.617	-0.905	-0.0738
	(0.575)	(0.715)	(0.709)
Ln(Total Wages)	2.021	5.132	5.920
	(6.332)	(9.444)	(5.830)
Ln(FHFA HPI Index)	-0.339	-0.988	-0.0716
	(0.711)	(1.071)	(1.086)
Observations	132	120	120
R^2	0.603	0.591	0.626

Bootstrapped standard errors are reported in parentheses. School and year fixed effects are included in all regressions. Treatment Group includes University of Arizona, Arizona State University, and Northern Arizona University. Control Group includes peer institutions.

Table 13: Estimated AIMS Effect on Retention Rates

	(1) Retention	(2) Retention
AIMS Effect	0.0170	0.115
	(0.333)	(0.533)
Ln(Unemp)		2.464
		(1.871)
Ln(Total Wages)		-20.41
		(14.96)
Ln(FHFA HPI Index)		0.956
		(1.688)
Observations	115	115
R^2	0.424	0.479

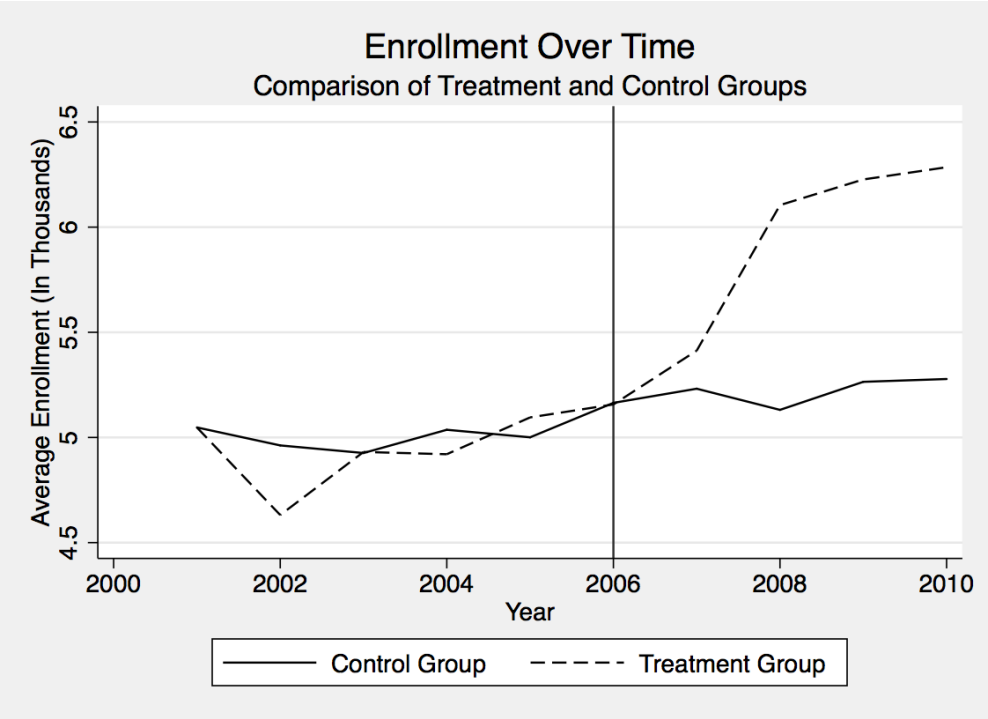
Bootstrapped standard errors are reported in parentheses. School and year fixed effects are included in all regressions. Treatment Group includes UA, ASU and NAU. Control Group includes peer institutions.

Table 14: Estimated AIMS Effect on In State Tuition and Fees

	(1) Tuition	(2) Tuition	(3) Tuition
AIMS Effect	0.160***	0.195***	0.169***
	(0.0344)	(0.0246)	(0.0254)
Ln(H.S. Grad)	0.211		0.259***
	(0.166)		(0.0975)
Ln(Unemp)		-0.187*	-0.203*
		(0.110)	(0.117)
Ln(Total Wages)		2.138***	2.113***
		(0.618)	(0.793)
Ln(FHFA HPI Index)		-0.572***	-0.582***
		(0.108)	(0.130)
Observations	169	170	169
R^2	0.921	0.944	0.945

Bootstrapped standard errors are reported in parentheses. School and year fixed effects are included in all regressions. Treatment Group includes UA, ASU and NAU. Control Group includes peer institutions.

Figure 1: Average First-Year First-Time Enrollment and In-State Tuition and Fees: Comparison of the Treatment and Control Groups



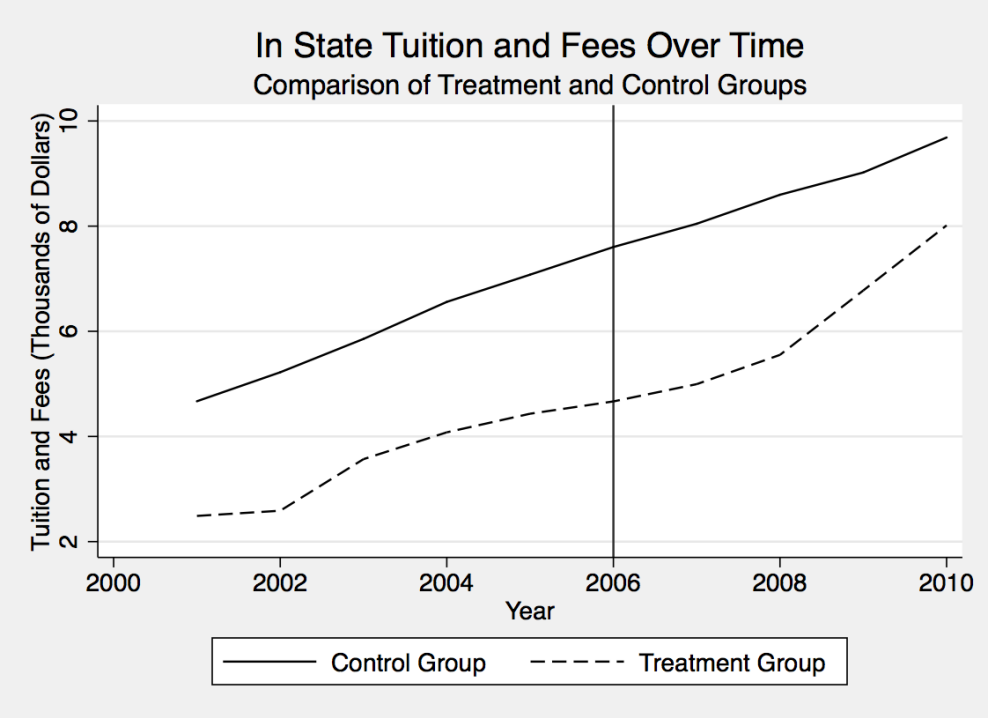
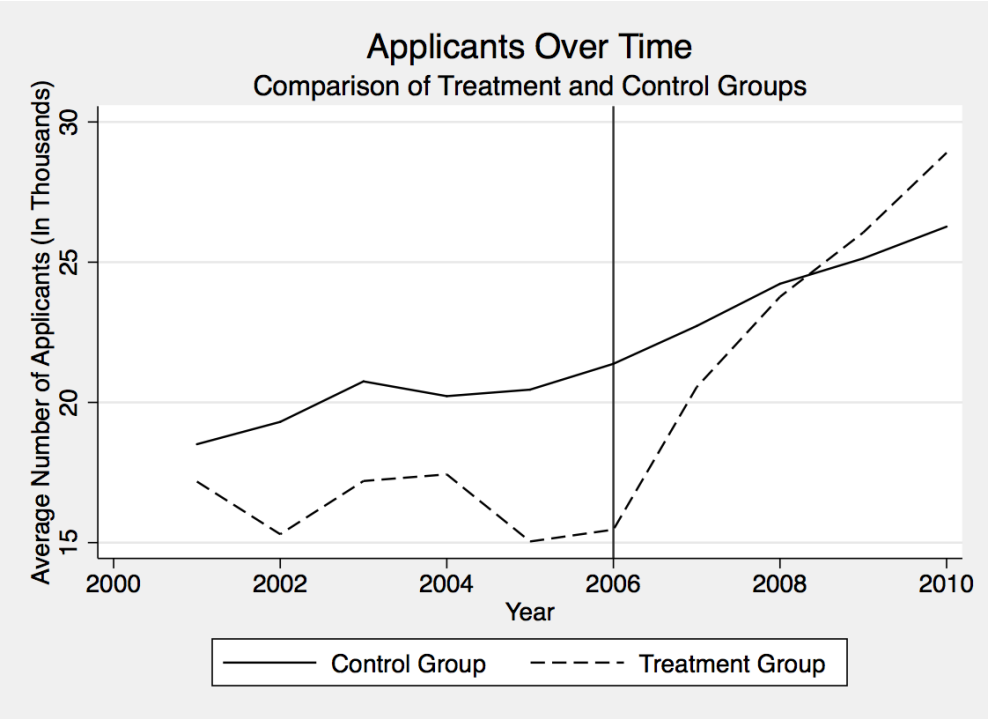


Figure 2: Average number of Applicants and Student Admissions: Comparison of the Treatment and Control Groups



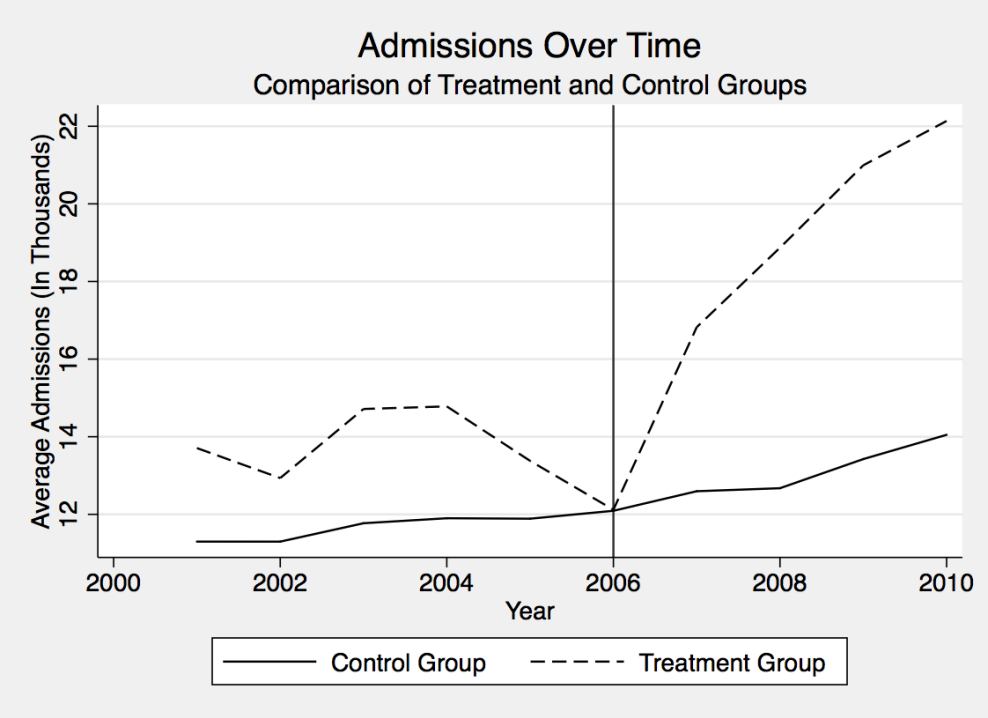


Figure 3: Enrollment By Race

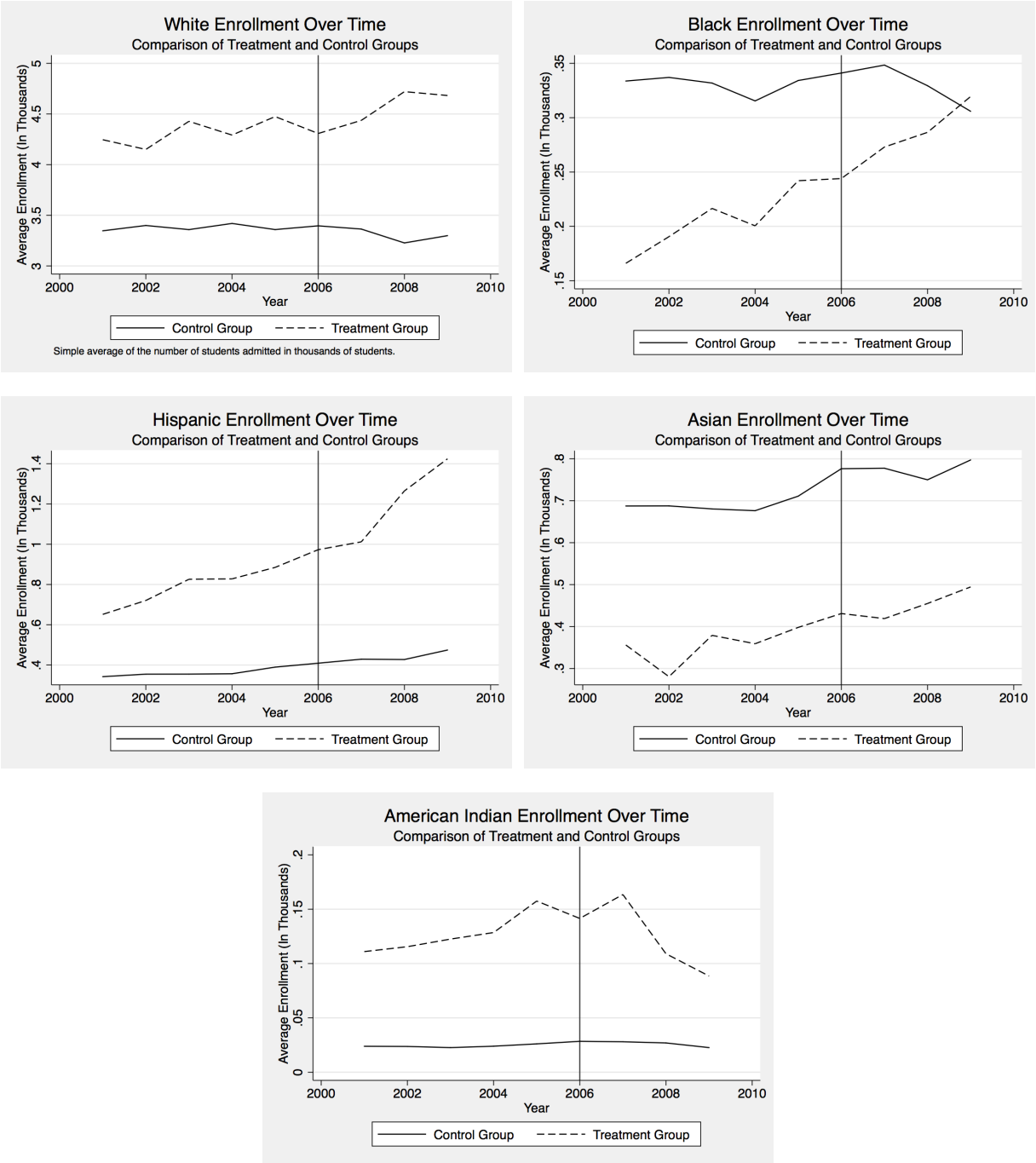
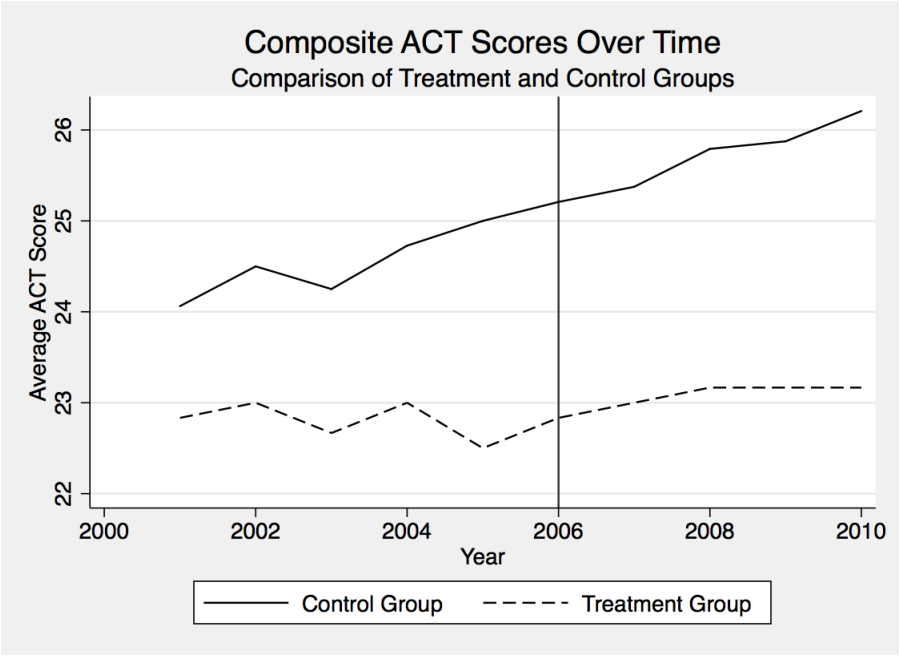


Figure 4: ACT Scores and Retention Rates



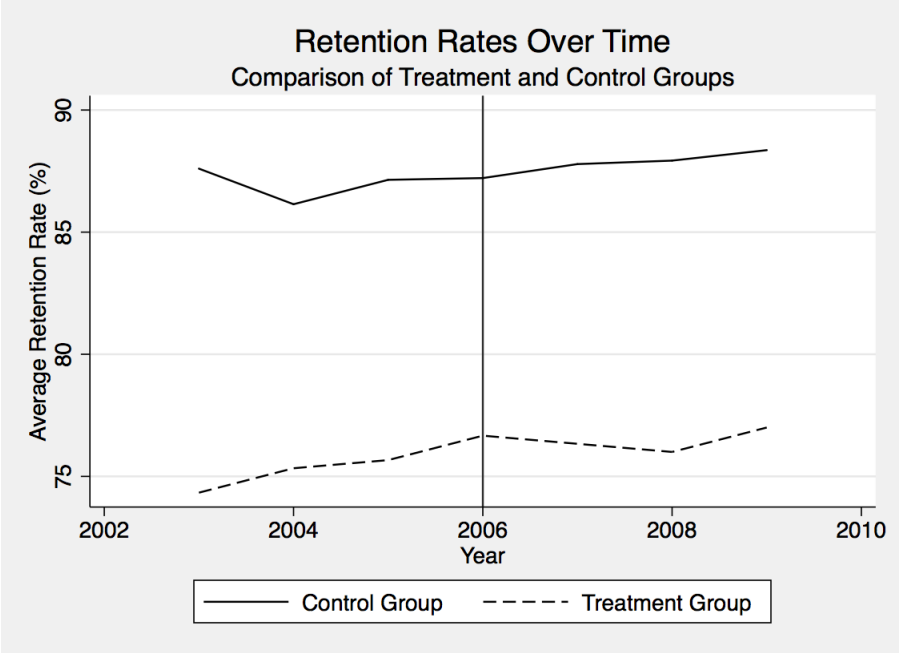
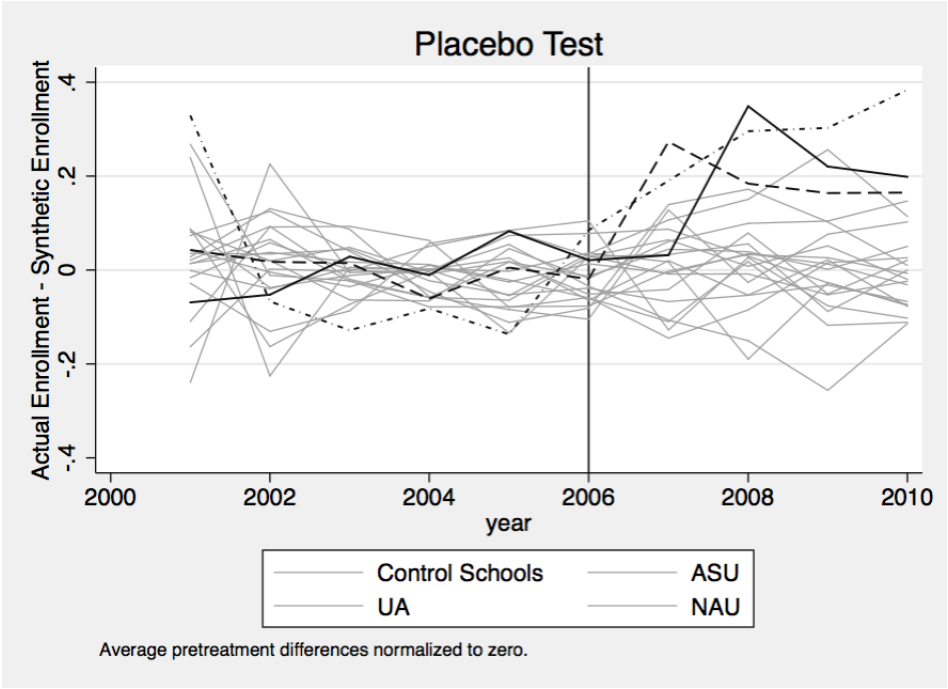


Figure 5: Enrollment and tuition gaps at Arizona schools and placebo gaps in non-Arizona schools.



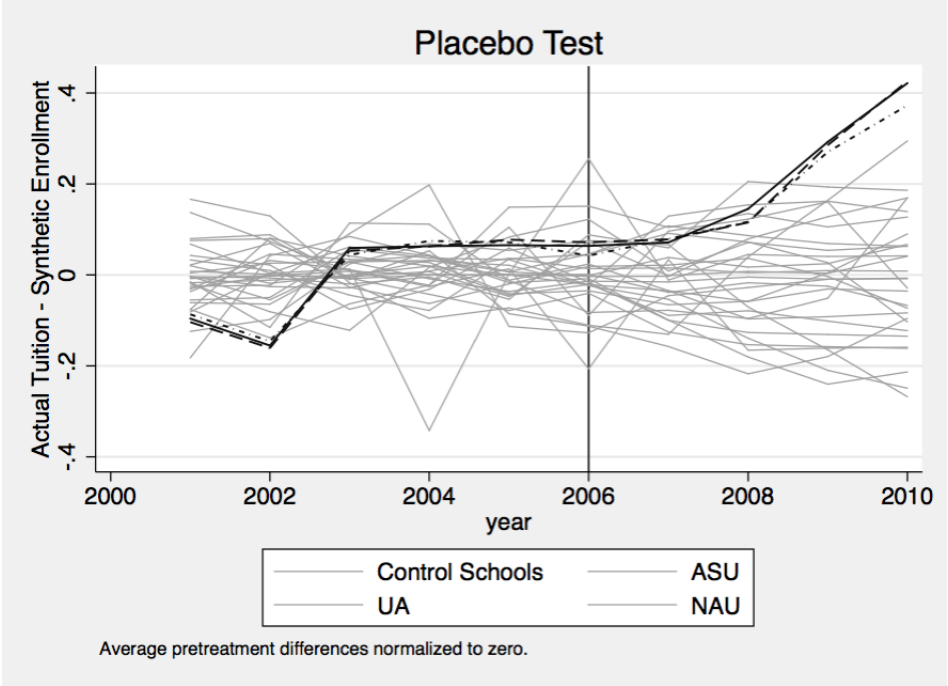
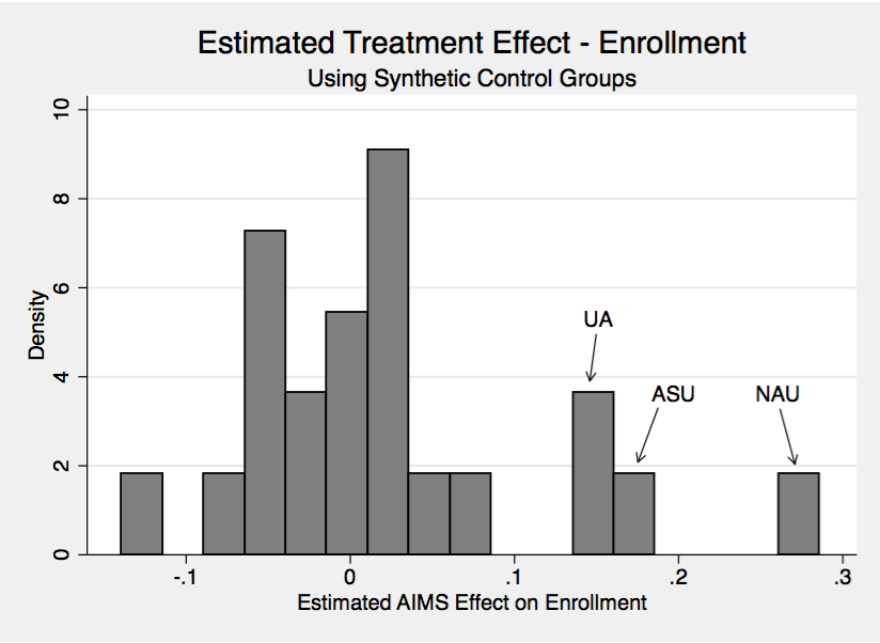
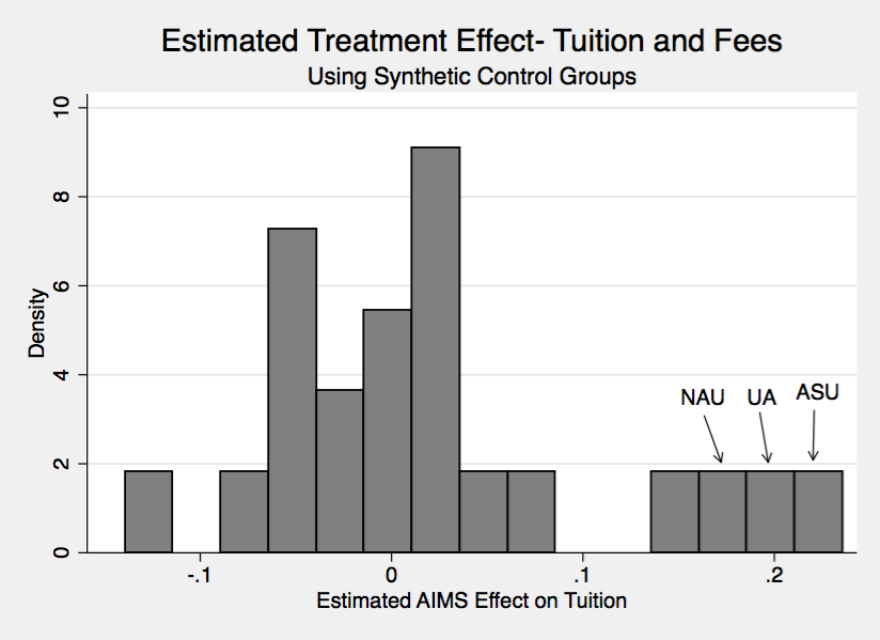


Figure 6: Histograms of estimated treatment effects for Arizona schools and non-Arizona placebo schools.





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