Need-Based Financial Aid for the "Not Too Needy": An Analysis of the Middle Class Scholarship of California*

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February 2024

I present new evidence on the effects of need-based grant programs for the middle-class. Using data from the National Association of State Student Grant Aid Programs and the Integrated Postsecondary Education System from 2011-2019, I use a synthetic difference-in-differences approach to estimate effects of the first major need-based program in California, the Middle Class Scholarship Program of 2015. I compare outcomes at University of California and California State schools to synthetic outcomes at other public universities in the United States. I evaluate total enrollments and graduation rates before and after program introduction. I find the middle class need-based program increased total enrollments by 3% and graduation rates by 6% per year on average.

I. Introduction

There is a continued debate over how much support states and the federal government should provide for higher education and in what form. At times, this debate is specifically over how much responsibility the federal government should take and how much the state government should take. In other instances, this debate is over how much aid should be awarded on the basis of merit or the basis of need. What informs these decisions is generally the effectiveness of the aid programs in both the short term and the long term. In the short term, the aid programs should be increasing college enrollments, persistence, and degree completion. In the long term, this should correlate to healthier

* I thank Dr. Analisa Packham, Dr. Michelle Marcus, Dr. Andrea Moro of Vanderbilt University for their guidance, helpful discussions, and suggestions throughout the production of this paper.

students, happier students, or more long term wealth. Another important factor in determining the value of an aid program is how effective the program is at lessening some systematic gap – generally the education gap between the lower and upper class. However, focusing on lessening the gap has generally led to a focus on the two extremes of the socioeconomic classes. The middle class may therefore be systematically excluded from the majority of aid programs and hence disadvantaged. Most of the existing need-based programs serve those of the lowest socioeconomic classes while those in the middle class are expected to likely receive aid through merit-based programs or fund college on their own, lacking the need for any aid at all. While it is widely shown that merit scholarships are awarded disproportionately to those in the middle and higher classes (Glater, 2017; Heller and Marin, 2002; Taylor and Cantwell, 2019), this does not directly translate to the majority of middle-class students receiving enough merit aid to successfully complete college. There remains the question that many middle class students may be just above the income cut off for need-based aid but not receiving any or enough merit aid. This paper examines the effects of need-based aid on the middle-class in order to provide insight into the proportion of middle-class students that are still in need, even with the existing merit-based programs that serve them.

I consider the first major solely need-based scholarship implemented in California in 2015 – the Middle Class Scholarship Program (MCS). This program aids families of income up to $217,000, a much higher cut off than the large majority of existing programs. Using the National Association of State Student Grant Aid Programs (NASSGAP) query tool, I identify this program as one of the need-based programs with the highest income cut-off. I further use NASSGAP to find details about MCS such as the implementation date, the considerations for award recipients, and the magnitude of award dollars distributed. Since MCS was implemented in 2015, I then use data from the Integrated Postsecondary Education System from 2011-2019 (National Center for Education Studies) and a synthetic difference-in-differences design to evaluate the effectiveness of the program by comparing outcomes in California to outcomes in other states. My findings that MCS increases total enrollments by 3% and graduation rates by 6% suggest that need-based scholarships for the middle class are effective at fulfilling needs that the merit-based scholarships or other grants are not. As the U.S. claims that increasing the college attendance of those in financial need is a significant priority, it is important to note that the middle-class *is* such a class in financial need but may be currently overlooked.

This paper will proceed as follows. In Section 2, I will review the existing literature surrounding need-based state grants and the middle class. I will then provide background on the Middle Class Scholarship program before introducing my empirical approach. In Section 4, I will present and discuss my results. Lastly, I will offer concluding remarks on the analysis of my results and their relation to current policy trends before finally making recommendations for future research.

II. Background

A. Existing Literature

There exists a large body of research evaluating how state grant aid programs affect residential migration, enrollment, or degree attainment of various categories of students, with mixed conclusions. One potential reason for these disparate findings is that effects depend on the format of the grant aid program, which varies substantially across states. First, state grant aid is generally merit-based or need-based, while some are a combination of the two. Merit based grants use measures of academic achievement such as GPA, standardized test scores, or the holding of certain titles such as the National Merit Scholar (Upton, 2016 & Sjoquist and Winters, 2015). In contrast, need-based grants use measures of need such as the Expected Family Contribution calculated from the information on family income, assets, and composition reported to the Free Application for Federal Student Aid (J. Chen & Hossler, 2017).

The majority of existing literature on need-based aid studies how such aid affects students of low socioeconomic status, as these are the communities the aid is generally intended for. Well studied programs include the Illinois Monetary Award Program (MAP), the Social Security Student Benefit Program, the Pell grant, and the Wisconsin Scholars Grant, all of which are programs intended for families at or below the poverty line. Feeney and Heroff (2013) find the Illinois MAP to have consistently positive effects on college enrollment, persistence, and graduation rates. Dynarski (2003) uses a natural experiment resulting from the demise of the Social Security Student Benefit Program and finds a 25 percentage point increase in the probability of college attendance when need-based aid eligible. However, both programs give to the neediest first and, with obviously limited funding, leave the middle class widely ineligible and unassisted.

There is an abundance of research on the "forgotten middle" in various sectors of life. Pearson and Quinn find that 54% of senior citizens belonging to the middle class will not have sufficient funds to obtain the care they will need in their later years (2009). Programs exist to help fund senior care for those of low socioeconomic status but not for those in the middle class. Swartz finds that in early adolescence, the middle class is the most widely uninsured class, more than the lowest socioeconomic classes, due to lack of government intervention (2006). Finally, Baum confirms an "emerging perception" among students of the middle class that their higher education opportunities are restricted (1994).

While the exact numbers vary by state and specific program, need-based aid is generally only given to those at, below, or very near the poverty line. Even if the program does not explicitly state this requirement, funds are given to the neediest first and run out before reaching the middle class. While some of the middle class can make up for this lack of need-based aid with the merit-aid they receive, many students do not qualify for merit-aid or the amount they do qualify for is not enough. Simply because the majority of merit-aid is awarded to middle and higher class students does not mean the majority of the middle class is receiving substantial merit-aid. In this paper, I contribute to the existing literature regarding the effectiveness of need-based aid programs by analyzing their effects on a different population. I further contribute to the existing literature on "the forgotten middle". Specifically, I add to current debate on whether students of middle-class have restricted higher education opportunities by studying the effects of a rare need-based aid program for the middle class.

B. The Middle Class Scholarship Program

In 2015, the Middle Class Scholarship Program (MCS) was implemented as the first solely need-based grant program in California[1]. MCS provides all California residents of the middle class a scholarship to attend either a University of California school or a California State University. The only requirements are California residency and a maximum family income of up to $217,000. While there is no lower bound cut off for income, the California Student Aid Commission publishes the income distribution of recipients each year, and it is clear that this program is assisting those of the middle-class rather than those of the lower-class. Specific income distributions for recipients of MCS in 2019, the most recent year in my study, can be found in Appendix Table A6. The application for the scholarship requires the student to complete the Free Application for Federal Student Aid (FAFSA) form or the CA Dream Act application which calculates information about their family's income and assets. Upon selection, the student will receive a grant award from the state of California to be used toward higher education. These awards can range from as low as 10% of cost of attendance to as high as 40% annually for up to four years, matching the student's "need", as defined by the program. Such definition is the cost of attendance after subtracting other gift aid the student is eligible for, a parent contribution for dependents with a household income over $100,000, and a $7,898 self-help

[1]The Law Enforcement Personnel Dependents Grant Program was implemented before this in 2003 but is specifically targeted to assist either dependents and spouses of California law enforcement or dependents and spouses of fire fighters killed or disabled while actively serving and only serves 13 recipients per year on average.

contribution. The parent contribution varies by student and is dependent upon parents' income while the $7,898 "self-help contribution" requirement is applied to all students, regardless of income or need. Students can make up this contribution through work-study on campus or other off-campus jobs.

Since 2015, MCS has awarded an average of $88 million per year, split between 56,000 students per year (NAASGAP). The program requires general funding provided by the state, which also sets the program's eligibility requirements and selects recipients. Intuitively, and in line with existing literature, I expect MCS to cause an increase in enrollments and graduation rates at University of California and California State schools. Not only should the program directly increase these outcomes by sending its recipients to college who may have not otherwise been financially able but should also have effects on those students on the margin of the 2 year to 4 year college decision or the workforce to college decision. Further, the program might shift those students planning on attending an out of state college or private CA university to attend a UC or CSU institution.

III. Empirical Approach

A. *Data*

For my main analysis, I use data from the Integrated Postsecondary Education Data System (IPEDS) from 2010 to 2019. This data exists at the institutional level and includes each institution's total fall enrollments and total degrees awarded for each year specified by major. Additionally, the data contains information on total graduations. I create a measure for graduation rates, defined as the rate of graduation for first-time full-time students. This rate is calculated by dividing the total number of graduates in a specific year that graduated within 6 years (150% of normal time) by the size of that year's incoming cohort. Since MCS is specifically intended for University of California schools and California State Universities, I include all UCs and CSUs in my treatment group. From here on, this group of UCs and CSUs will be referred to as "California schools", but does not include private or other public institutions.

For my primary method, I filter for all U.S. public four-year institutions to produce a panel data set of 734 institutions. In secondary methods, I form comparison groups using only states in the Western Interstate Commission for Higher Education (WICHE) and only California's bordering states. The WICHE was created in 1953 when Congress approved the Western Regional Education Compact, a compact among 15 western states – Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, Nevada, New Mexico, North Dakota, Oregon, South Dakota, Utah, Washington, and Wyoming. This compact authorized the creation of a commission with congressional consent to specifically work toward improving the quality of higher education and expand the opportunities for those seeking higher education. More specifically, I use those WICHE states that did not have significant program implementations for at least 5 years before MCS' implementation or throughout the analyzed time (2010-2019). This excludes Colorado, Hawaii, Nevada, New Mexico, North Dakota, South Dakota, and Washington, leaving Arizona, Oregon, Alaska, Idaho, Montana, Utah, and Wyoming producing a panel data set of 69 institutions. While the WICHE has no authority to require policy enactment in any state, they do advise all 15 states and therefore the larger policy changes that occur in 1 of the states generally occur in the other 14. Therefore, one would expect the students at schools incorporated in WICHE to serve as a good comparison group for students in California. I also perform tests using California's bordering states, Arizona and Oregon, for robustness. I exclude Nevada due to its implementation of a need-based program in 2016. For my analysis with the bordering states comparison group, I use a panel data set of 40 institutions.

B. *Identification Strategies*

I use two approaches to measure the effects of MCS. First, I use a difference-in-differences estimation approach to compare total enrollments and graduation rates before the program implementation year to total enrollments and graduation rates after the implementation year. I begin by analyzing total enrollments and graduation rates and expand upon my work by analyzing these outcomes by gender. I derive specifications using the eligible WICHE states as a control group and the eligible bordering states as a control group for robustness. To estimate average effects of each grant program, I estimate the following regression model using ordinary least squares:

$$(1)\ Outcome_{ist} = p_t + m_s + d\ Post_t * Treat_s + u_{ist},$$

where $Outcomet_{ist}$ is the total number of students enrolled at institution *i* in state *s* at time *t* or the graduation rate at institution *i* in state *s* at time *t*. p_t accounts for year fixed effects, and m_s accounts for state fixed effects. *d* is the coefficient of interest and can be interpreted as the average effect of program implementation. In the case of the total enrollments analysis, *d* will be interpreted as the additional number of students enrolled in a California school per year on average, relative to the counterfactual. In the case of the graduation rate analysis, *d* will be interpreted as the percentage point increase in graduation rate at a California school per year on average, relative to the counterfactual. *Post* is a dummy variable taking a value of 1 for years equal to or later than the implementation year and 0 otherwise. When analyzing both outcomes, the implementation year is 2015, the year of program introduction. Graduation rates each year are calculated as the combined rate of all those graduating within 6 years of enrolling per that year's enrollment cohort. Therefore, since MCS was implemented in 2015 and 31% of funds were awarded to seniors, the grant theoretically could have had an effect as on graduation rates as early as 2015. *Treat* is a dummy variable taking a value of 1 for schools in California and equal to 0 for schools in any of the control states. I calculate standard errors clustered at the state level, the level of treatment.

Second, I use a data-driven method to construct a comparison group that provides additional estimates of the effects of MCS on student outcomes. Using a synthetic difference-in-differences (SDID) estimation approach, I compare enrollments and graduation rates in California Schools before the program implementation year to the same outcomes in my comparison group after the implementation year. I derive this potential counterfactual using the SDID procedure implemented by Arkhangelsky at al. (2021). Specifically, since the funds from the program became available to all UC and CSU schools at the same time, I use a block treatment assignment with a block bootstrap variance estimation. To estimate the average treatment effect of MCS on such California schools, I estimate the following two-way fixed effects regression:

$$(2)\ (\hat{G}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \underset{\mathrm{G},\mu,\alpha,\beta}{\operatorname{argmin}} \left\{ \sum_{i=1}^{N} \sum_{i=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\mathrm{G})^2 \widehat{w_i^{sd\imath d}} \widehat{\lambda_t^{sd\imath d}} \right\}$$

where G is the average treatment on the treated. Y_{it} represents total enrollments or graduation rate for each institution i at each time t. μ represents some constant, α_i represents some institution fixed effect, and β_t represents some time fixed effect. W_{it} denotes a dummy variable for treatment, equal to 1 if the institution i is treated at time t and equal to 0 if not. The model requires a balanced panel data set of N units observed over T time periods. Here, N=7934 institutions and T=8, as outcomes are observed from 2011-2019. The model mimics a standard difference-in-difference model almost exactly with the exception of added $\widehat{w_i^{sd\imath d}}$ and $\widehat{\lambda_t^{sd\imath d}}$ which are optimally chosen weights. While the standard DID model places equal weights on all counterfactual units, SDID allows for the violation of the parallel trend assumption by creating its own synthetic control group that satisfies the assumption. Unit weights, w, ensure the synthetic control group is generated based on the schools that were enrolling or facing degree attainments at similar rates as California schools prior to treatment while time weights, λ, ensure the most weight is placed on the most similar pre-treatment periods. More specifically, for unit weights, penalized least squares are used to construct a weighted average of control units and produce a synthetic unit with a pre-treatment trend parallel to the average trend of the treated units. Importantly, this regression allows for a constant term so that the construction of weights does not require each state to be in the convex hull of the other states. The process is almost identical for construction of time weights, but the unit weight construction uses ridge regression regularization while the time weight does not. This allows for the weights to be more loaded toward recent time periods and zeroed out in earlier time periods.

The identification assumption underlying both of these approaches is that in the absence of treatment, outcomes would continue to trend in the treatment group similarly to the outcomes in the comparison group. While I show below that this assumption is unlikely to hold in the context of a simple difference-in-differences approach, I show that this assumption *is* likely to hold when using my synthetic control approach. I provide support for this identification assumption in two main ways. First, I show that trends in the outcome variables are similar for treatment and comparison groups prior to the MCS implementation year. This provides support for the notion that other schools would have experienced similar trajectories of student enrollments and graduation rates in the absence of the program. Second, I note that no other policy changes happened concurrently that would have changed enrollments in California, relative to the constructed weighted comparison group.

IV. Results

This section proceeds with an analysis of the effects of MCS on total undergraduate enrollments and undergraduate graduation rates. Below, I present my analysis of total undergraduate enrollments, stating my methods in detail. I then present my analysis of graduation rates following the same methods.

IV.1 Analysis of Total Undergraduate Enrollments

A. DID Design

First, I present a graphical analysis of the raw data trends. Figure 1 plots the average total enrollments across University of California and California State institutions against average total enrollments across other eligible WICHE states. Figure 2 plots the average total enrollments across University of California and California State institutions against average total enrollments across other eligible bordering states.

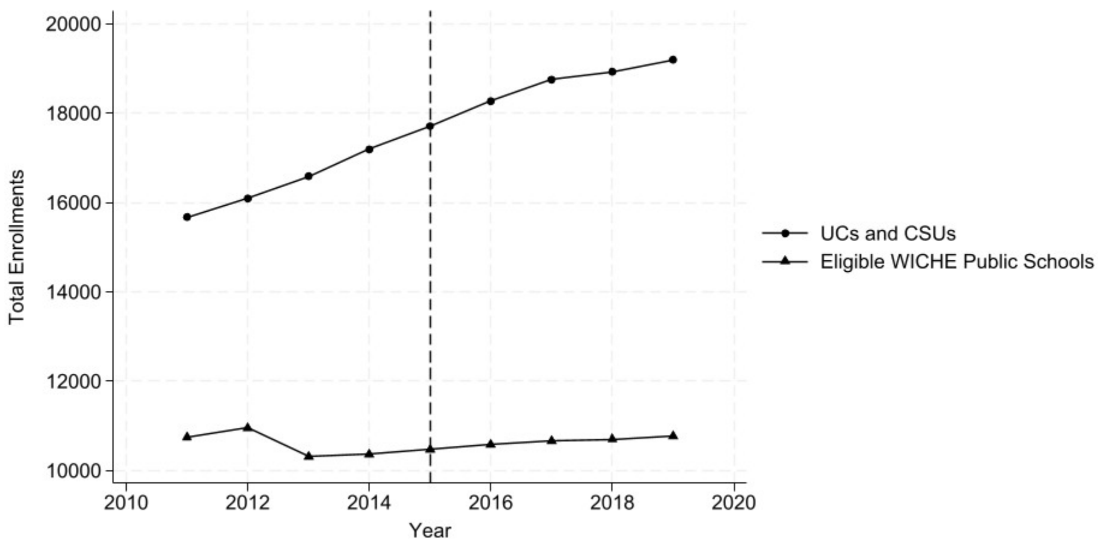


FIGURE 1. TOTAL ENROLLMENTS IN CALIFORNIA VS. OTHER ELIGIBLE WICHE STATES

Notes: The vertical line, drawn at 2015 represents the year the need-based program was implemented. Each circle dot represents the average total enrollments of the corresponding year for all California schools. Each triangle dot represents the average total enrollments of the corresponding year for all other eligible WICHE schools. The eligible WICHE includes Arizona, Oregon, Alaska, Idaho, Montana, Utah, and Wyoming

Source: Annual data on total enrollments by institution and year provided by the Integrated Post-Secondary Education System.

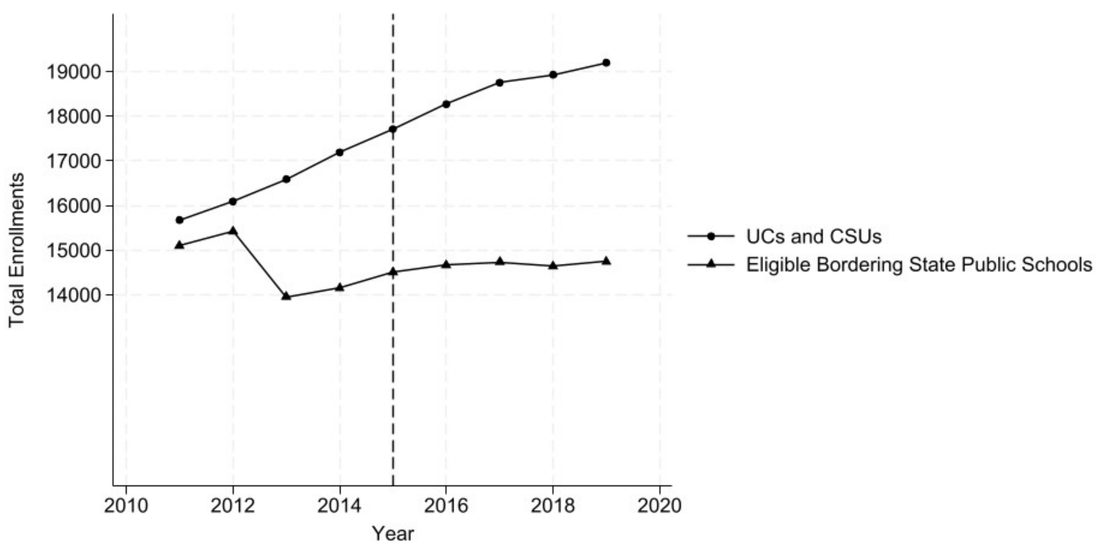


FIGURE 2. TOTAL ENROLLMENTS IN CALIFORNIA VS. OTHER ELIGIBLE BORDERING STATES

Notes: The vertical line, drawn at 2015 represents the year the need-based program was implemented. Each circle dot represents the average total enrollments of the corresponding year for all California schools. Each triangle dot represents the average total enrollments of the corresponding year for all other eligible bordering state schools. The eligible bordering states include Arizona and Oregon.

Source: See Figure 1.

In both figures, it can be seen that the treatment group is not trending similarly to the comparison group before treatment implementation. Therefore, it would not be correct to conclude the divergence of trends in the post-period is due to the treatment. This motivates the use of a synthetic control group which will likely satisfy the necessary identification assumption. Table 1 displays the difference-in-difference estimates obtained from the model described in equation (1). Column 1 presents the estimates obtained when using eligible WICHE states as a counterfactual. Column 2 presents the estimates obtained when using eligible bordering states as a counterfactual. However, since there is evidence of an identification assumption violation, these estimates should not be trusted.

TABLE 1. OLS ESTIMATES OF THE EFFECT OF THE MIDDLE CLASS SCHOALRSHIP ON TOTAL ENROLLMENTS

	(1)	(2)
Effect of MCS	2138.44	2183.88
P Value	0.000	0.000
95% Confidence Interval	[1701.51, 2575.36]	[1486.06, 2881.70]
Observations	657	387
Year fixed effects	Yes	Yes
Institution fixed effects	Yes	Yes
Comparison Group	Eligible WICHE states	Eligible Bordering states

Notes: Estimates are based on annual data on institutions from 2011-2019 and obtained from the model described in equation (1). Column 1 estimates use eligible WICHE states as a counterfactual to the treatment group in California. These states include Arizona, Oregon, Alaska, Idaho, Montana, Utah, and Wyoming. Column 2 estimates use eligible bordering states as a counterfactual to the treatment group in California. These states include Arizona and Oregon.

When using eligible WICHE states as a counterfactual, the DID design finds that the implementation of MCS increases total enrollments at UCs and CSUs by 2,138 students on average. When using eligible bordering states, this estimate is closer to 2,184. Both estimates are statistically significant and relatively close in value, which should provide confidence in their validity. However, with evidence that the treatment group was trending differently than the comparison group even before treatment, I cannot conclude that the divergence of trends is due to the treatment. Therefore, I proceed to use an SDID design, synthetically construct a comparison group that *will* trend similarly to the treatment group in the pre-period, and therefore produce estimates that *can* be trusted.

B. SDID Design

In this section, I present estimates from a data-driven method of synthetic control which allows me to construct a valid counterfactual and more accurately measure how enrollments would have changed in the absence of the Middle Class Scholarship. Here, I present a graphical analysis of the data trends produced by the "synthetic California" I created according to the methodology described in Section II. Figure 3 plots the average total enrollments across University of California and California State institutions against average total enrollments across "synthetic California".

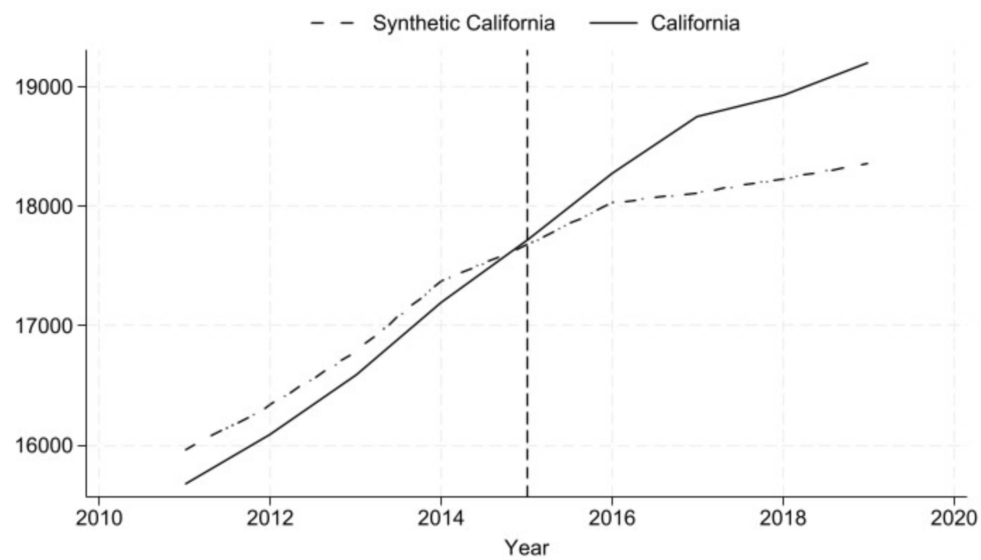


FIGURE 3. TOTAL ENROLLMENTS IN CALIFORNIA VS "SYNTHETIC CALIFORNIA"

Notes: The vertical line, drawn at 2015 represents the year the need-based program was implemented.
Source: See Figure 1.

"Synthetic California" trends are generated through a weighted average of enrollments of institutions in all other 49 states. Notably, and by construction, the trends before 2015 are relatively parallel. This supports the assumption that total enrollments in California states grew at the same rate as total enrollments in the synthetic state prior to treatment. Therefore, is it reasonable to presume the growth of total enrollments in states after 2015 will provide a good counterfactual to my treatment group. Importantly, the trends diverge after 2015 which provides initial evidence that MCS did increase enrollments for the schools in California.

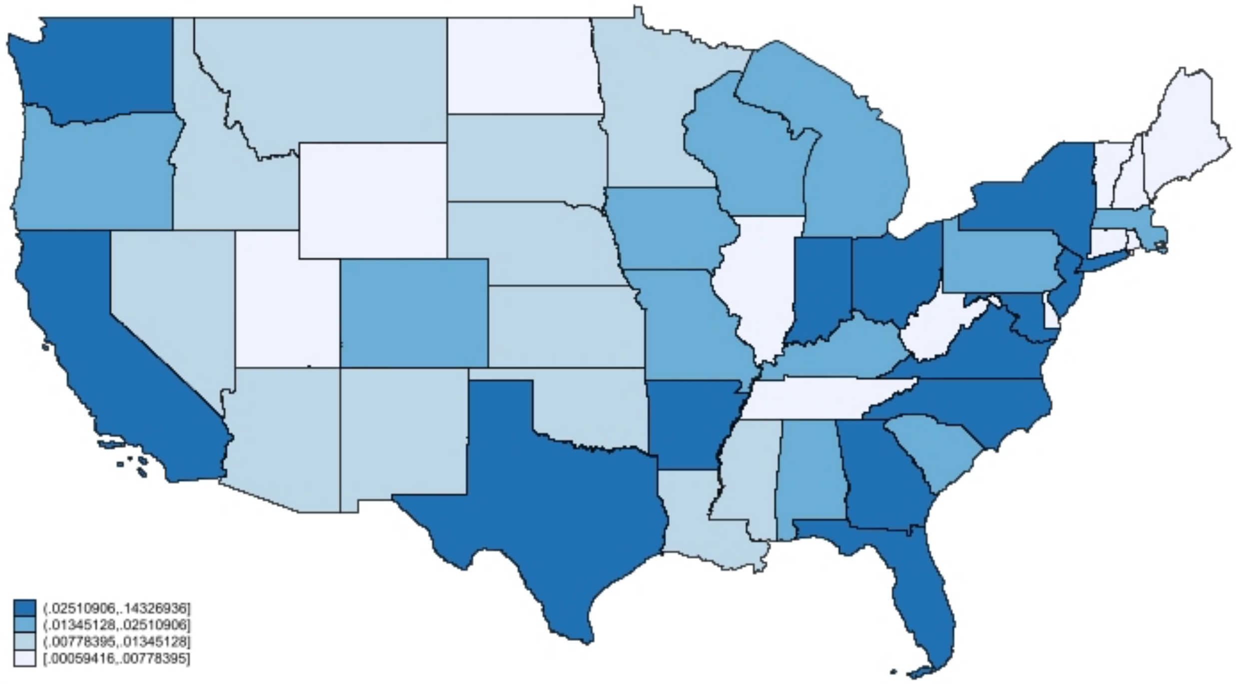


FIGURE 4. RELATIVE WEIGHTS ASSIGNED TO FORM "SYNTHETIC CALIFORNIA"

Notes: To form Synthetic California, a different amount of weight is put on each institution in the panel data set. Weights are then summed across all institutions in each particular state to determine how much influence each state has on Synthetic California.

Source: Annual data on total enrollments by institution and year provided by the Integrated Post-Secondary Education System. US Map shapefile provided by ScienceBaseCatalog.gov.

Table A1 shows the weights assigned to the 10 most highly weighted institutions in order to make up "Synthetic California", and the graph above, Figure 4, gives a visual representation. Notably, the largest weights seem to not necessarily be California's bordering states but rather other states that are similarly on the coast.

Table 2 displays the synthetic difference-in-difference estimates obtained from the model described in equation (2).

TABLE 2. SYNTHETIC ESTIMATES OF THE EFFECT OF THE MIDDLE CLASS SCHOALRSHIP ON TOTAL ENROLLMENTS

	(1)
ATT	672.59
Percent Effect of MCS	3.23%
P Value	0.003
95% Confidence Interval	[235.96, 1110.23]
Std. Error	222.78

Notes: Estimates are based on annual data on institutions from 2011-2019 and obtained from the model described in equation (2).

Synthetic estimates show the need-based program increased total enrollments at California schools by 3.23% over the 5 years after program adoption. Percent effect is calculated by dividing the absolute increase by the mean total enrollments which can be found in Table A2, a summary statistic table. This estimate is statistically significant shown with P-value of 0.004 and this percentage corresponds to an increase of 673 students per institution per year. An enrollment effect of 673 students per institution year over the 5 years after program introduction accounts for 28.5% of recipients of the scholarship. This percentage of representation is estimated by historical reports produced by the California State Aid Commission and data from NASSGAP. There exists 56,531 MCS recipients on average each year and I observe an average 673 student increase in total enrollments at each UC and CSU institution. Since there are 24 UC and CSU institutions in my panel data, I calculate a 28.5% accountability rate for MCS – the observed enrollment effects of the scholarship account for 28.4% of the recipients. In other words, about 16,000 students that receive MCS are then able to attend a UC or CSU institution that they would not have otherwise. This accountability rate is almost three times that of the Hope scholarship, one of the most prominent merit scholarships studied (Mustard and Sridhar, 2003).

C. By Gender Analysis

Here, I use my primary synthetic control approach to decompose MCS's total enrollment effects by gender[2]. The synthetic difference-in-differences analysis is presented below. Figures 5 and 6 present the trends for male and female enrollments respectively across UC and CSU universities versus the synthetic trends.

[2]With each analysis, I first perform DID to motivate my use of synthetic DID. However, since the pre-trend assumption is violated, these estimates are not valid. As they are only useful for motivation and not interpretation, I will reference these estimates and raw data trend graphs in the appendix from here on. Please refer to Appendix Figures A1-A4 for trends specific to each gender and Table A3 for those DID estimates.

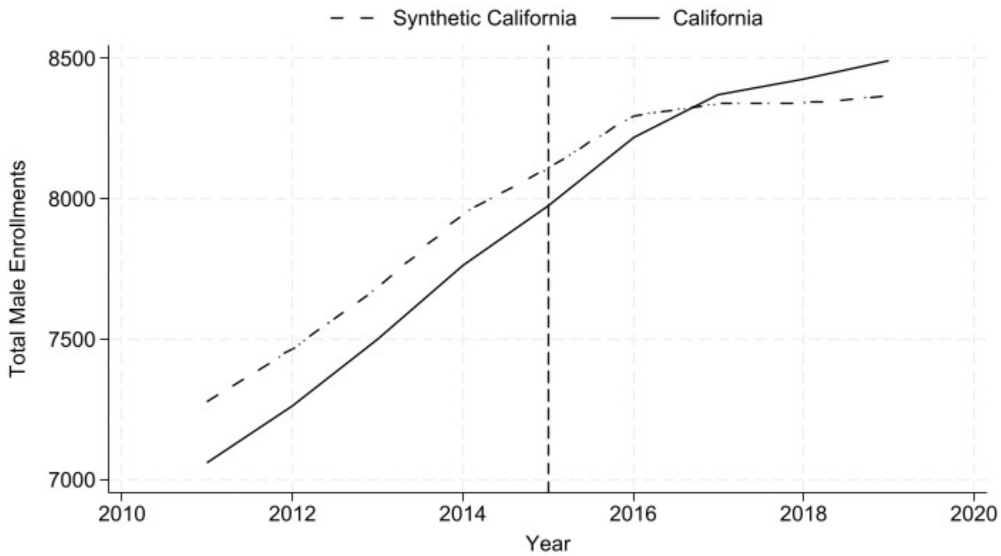


FIGURE 5. MALE ENROLLMENTS IN CALIFORNIA VS "SYNTHETIC CALIFORNIA"

Notes: The vertical line, drawn at 2015 represents the year the need-based program was implemented.
Source: See Figure 1.

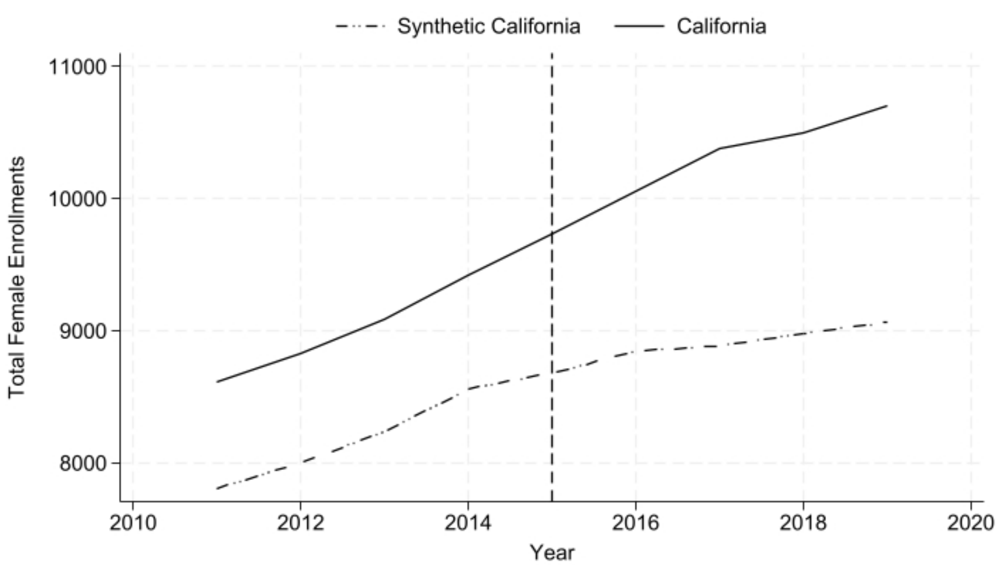


FIGURE 6. FEMALE ENROLLMENTS IN CALIFORNIA VS "SYNTHETIC CALIFORNIA"

Notes: The vertical line, drawn at 2015 represents the year the need-based program was implemented.
Source: See Figure 1

I estimate a "Synthetic California" trend as previously discussed in Section II. I first note that prior to 2015, the trends for California schools and synthetic California track similarly. Table 3 displays the synthetic difference-in-differences estimates obtained from the model described in equation (2). Column one presents the estimates for male enrollments while column 2 presents the estimates for female enrollments.

TABLE 3. SYNTHETIC ESTIMATES OF THE EFFECT OF THE MIDDLE CLASS SCHOALRSHIP ON TOTAL ENROLLMENTS

	(1)	(2)
	Male Students	Female Students
ATT	190.59	517.057
Percent Effect of MCS	2.45%	5.49%
P Value	0.018	0.000
95% Confidence Interval	[32.76, 348.46]	[267.6542, 766.45948]
Std. Error	80.544	127.24850

Notes: Estimates are based on annual data on institutions from 2011-2019 and obtained from the model described in equation (2).

Synthetic estimates show the need-based program increased male enrollments at California schools by 2.45% and female enrollments by 5.49% over the 5 years after program adoption. The percentages are again calculated by dividing ATT by gender specific average enrollments. Both estimates are statistically significant at the 5 percent level and estimates for female enrollments are significant at the 1 percent level. These percentages correspond to an increase of 191 male students per year, and 517 female students per year. The much larger effects for female over male students are interesting and could potentially be explained by the general make up of the scholarship recipients being almost 60% women and 40% men. However, since the confidence intervals do overlap for each gender, these differences are most likely not statistically significant.

IV.2 Analysis of Graduation Rates

This section proceeds identically to section III.1 but analyzes graduation rates rather than enrollments[3].

A. SDID Design

I present a graphical analysis of the data trends produced by the "synthetic California" I created. Figure 7 plots the average graduation rates across University of California and California State institutions against average graduation rates across "synthetic California".

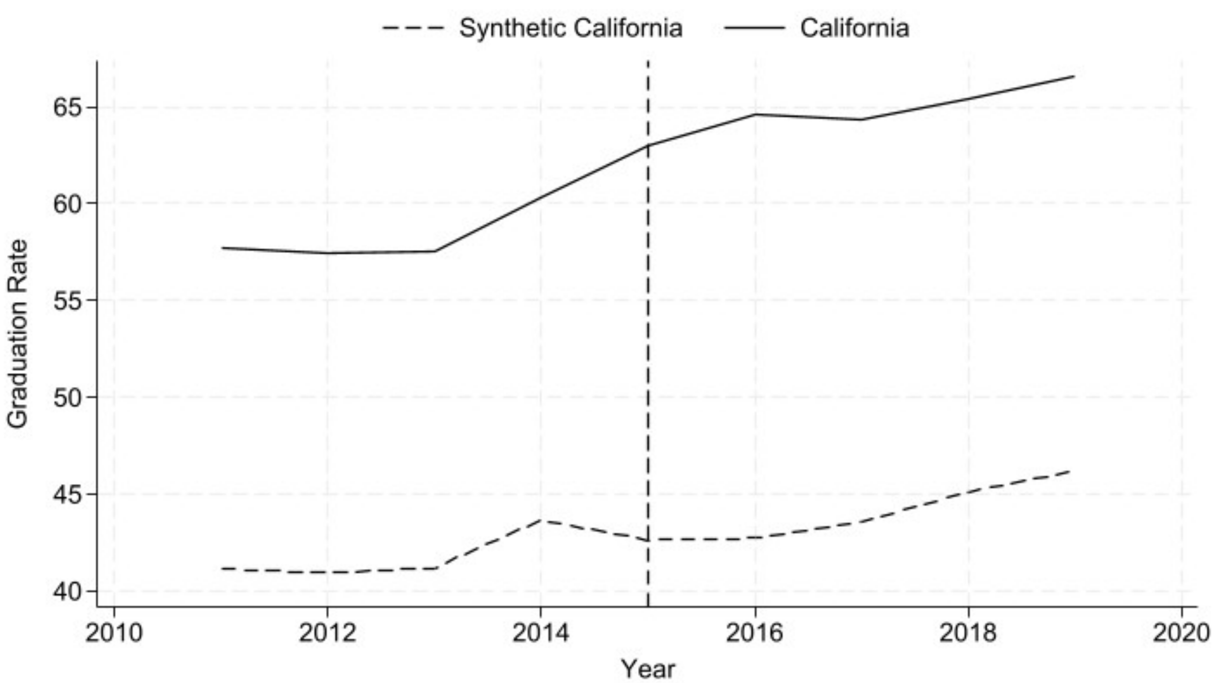


FIGURE 7. GRADUATION RATES IN CALIFORNIA VS "SYNTHETIC CALIFORNIA

Notes: The vertical line, drawn at 2016 represents the year the need-based program theoretically first began affecting graduation rates.
Source: See Figure 1

Table A1 shows the weights assigned to each state in order to make up "Synthetic California", and the graph below, Figure 8, gives a visual representation. Table 4 displays the synthetic difference-in-differences estimates obtained from the synthetic controls approach described in equation (2).

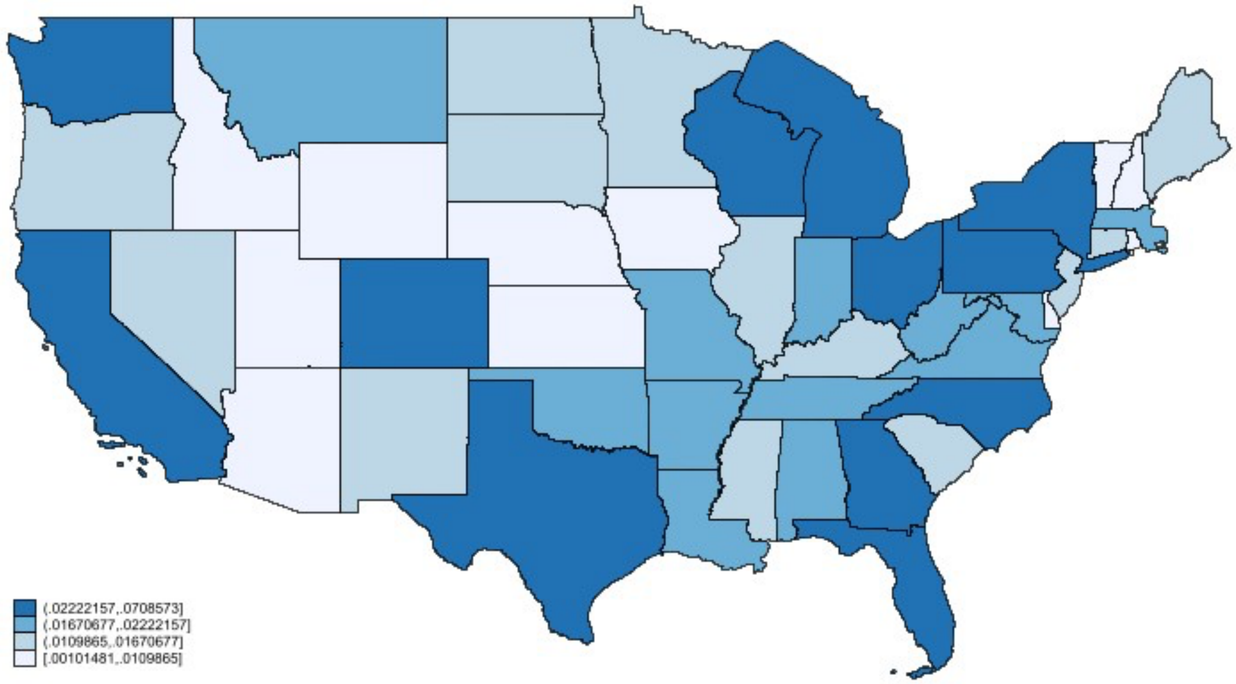


FIGURE 8. RELATIVE WEIGHTS ASSIGNED TO FORM “SYNTHETIC CALIFORNIA”

Notes: To form Synthetic California, a different amount of weight is put on each institution in the panel data set. Weights are then summed across all institutions in each particular state to determine how much influence each state has on Synthetic California.

Source: Annual data on total enrollments by institution and year provided by the Integrated Post-Secondary Education System. US Map shapefile provided by ScienceBaseCatalog.gov.

TABLE 4. SYNTHETIC ESTIMATES OF THE EFFECT OF THE MIDDLE CLASS SCHOALRSHIP ON GRADUATION RATES

	(1)
ATT	4.18
Percent Effect of MCS	6.44%
P Value	0.000
95% Confidence Interval	[2.39, 5.97]
Std. Error	0.91

Notes: Estimates are based on annual data on institutions from 2011-2019 and obtained from the model described in equation (2).

Synthetic control estimates show the need-based program increased graduation rates at California schools by 4.18 percentage points over the 5 years after program adoption. This estimate is statistically significant with P-value 0.000. While 4 percentage points may seem small, this is a surprisingly large effect considering all the circumstances that the program was implemented in 2015. There are two main reasons why a need-based aid program could affect graduation rates. First, the program could make it so that one who could not afford college before now is able. By simply making the student able to enroll and attend, the program is also increasing their chances of graduation. If the program is attracting the type of students that will graduate, then the program could increase the university's graduation rates. Second, the program could make it so that one already in college who comes into financial hardship or simply wants to quit, is influenced to stick it out. Since the MCS is awarded disproportionately to freshmen more than any other year, the majority of positive graduation rate effects I observe should be from the program attracting capable freshmen. However, the freshmen cohort outcomes are only measured once in my analysis – the 2019 graduation rate. The calculated graduation rate effect is therefore mainly made up by the seniors and juniors the program has affected. I expect this graduation rate effect to therefore be much larger in the upcoming years once the program is in effect for longer and affecting more freshmen enrollees.

B. By Gender Analysis

Here, I decompose MCS's graduation rate effects by gender. Figures 7 and 8 present the trends for male and female enrollments respectively across UC and CSU universities versus the synthetic trends.

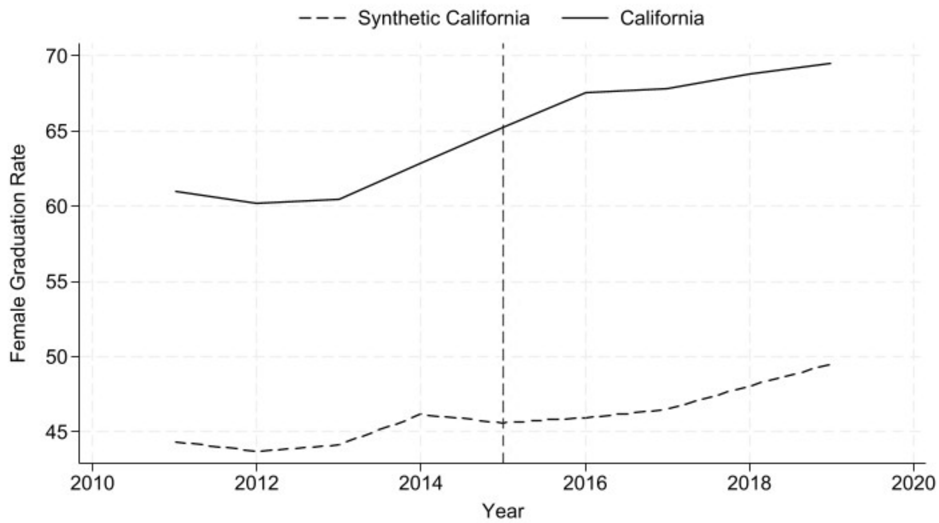


FIGURE 7. FEMALE GRADUATION RATES IN CALIFORNIA VS "SYNTHETIC CALIFORNIA"

Notes: The vertical line, drawn at 2016 represents the year the need-based program theoretically first began affecting graduation rates.
Source: See Figure 1

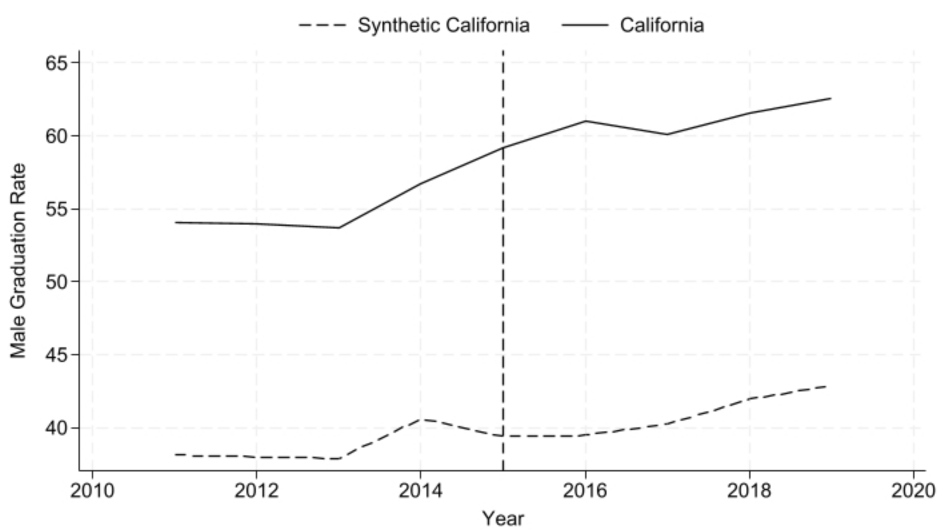


FIGURE 8. MALE GRADUATION RATES IN CALIFORNIA VS "SYNTHETIC CALIFORNIA"

Notes: The vertical line, drawn at 2016 represents the year the need-based program theoretically first began affecting graduation rates.
Source: See Figure 1

Again, noting the parallelism of the trends before 2015 to the divergence of the trends after 2015 allows for initial suspect that the program did have some effect on graduation rates for California schools. Table 5 displays the synthetic difference-in-difference estimates obtained from the model described in equation (2). Column one presents the estimates for male graduation rates while column 2 presents the estimates for female graduation rates.

TABLE 5. SYNTHETIC ESTIMATES OF THE EFFECT OF THE MIDDLE CLASS SCHOALRSHIP ON TOTAL ENROLLMENTS

	(1)	(2)
	Male students	Female students
ATT	4.13	4.10
Percent Effect of MCS	6.77%	6.04%
P Value	0.000	0.000
95% Confidence Interval	[2.46, 5.80]	[2.41, 5.79]
Std. Error	0.85	0.86

Notes: Estimates are based on annual data on institutions from 2011-2019 and obtained from the model described in equation (2).

Synthetic control estimates show the need-based program increased male graduation attainments at California schools by 4.13 percentage points and female graduation rates by 4.10 percentage points over the 5 years after program adoption. Both estimates are statistically significant at standard levels with low P values of 0.000.

V. Conclusion

Through an analysis of the first major solely need-based program in California and one of the only solely-need based programs with such a high income cutoff, this paper provides initial evidence for the effectiveness of need-based programs for the middle-class in terms of enrollments and graduation rates. While the lack of a valid counterfactual to produce DID estimates with raw data limits my results, through a data-driven construction of a synthetic control, I am able to make some valid conclusions. Estimates indicate that the middle-class need-based program increases enrollments and graduation rates by 3%.

There are limitations to note in my study. Firstly, my methodology relies on a balanced data set. While I have access to the data for the majority of institutions across the United States, there are several that had to be eliminated from the study due to their lack of reporting in certain years. Second, while the construction of my synthetic control group is data-driven, it remains synthetic. Future work should look to compare other middle-class need-based programs in which raw and valid counterfactuals exist. Raw and valid DID estimates will add robustness to the results I have obtained and further speak to the effectiveness and necessity of middle-class need-based programs. Future work could also include a regression-discontinuity design to evaluate the effectiveness of the program by comparing those right at the cutoff to those right below.

Noting the limitations, my results have important policy implications for increasing the effectiveness of student aid. While many currently theorize merit-aid is satisfying the needs students of the middle-class may have to successfully attend and graduate from college, I have shown need-based programs for the middle class are still producing effects. Therefore, there is some need still not being met for those in the middle-class. However, to truly gain a comprehensive sense of whether or not need-based aid is needed more for the middle class, we need to study long term effects for those who received need-based aid. By looking at long term wages, happiness, and health, we can say something about the true necessity of need-based aid for the middle class. More research and policy analyses are necessary to ensure the effective assistance to those in financial need pursuing a higher education.

V. Appendix

TABLE A1. WEIGHTS ASSIGNED TO THE HIGHEST CONTRIBUTING INSTITUTIONS TO MAKE UP SYNTHETIC CALIFORNIA

Institution	Enrollment Analysis
1- Texas A&M University – College Station	0.019
2- Indiana University – Bloomington	0.014
3- Florida International University	0.013
4- Iowa State University	0.012
5- Lone Star College System	0.012
6- The University of Alabama	0.012
7- University of Maryland Global Campus	0.011
8- Rutgers University – New Brunswick	0.010
9- Oregon State University	0.009
10- Texas State University	0.008
Institution	**Graduation Rate Analysis**
1- Stone Child College	0.011
2- Florida Gateway College	0.004
3- Dine College	0.004
4- Bellingham Technical College	0.003
5- Northwest Indian College	0.003
6- Ohio University – Eastern Campus	0.003
7- Tennessee State University	0.003
8- Eastern Oregon University	0.003
9- University of Illinois Springfield	0.003
10- Northwest College	0.003

Notes: There are two CA units above. Number 29, “CA*”, represents schools in California that are not a UC or CSU while Number 5, “CA”, represents all of the UC and CSU schools. Neither are used to construct “Synthetic California”.

TABLE A2. UC AND CSU SUMMARY STATISTICS

Enrollments	2015 Total Mean	2015 Male Mean	2015 Female Mean
	17711.7	7977	9734.7
Graduation Rates	2016 Total Mean	2016 Male Mean	2016 Female Mean
	64.86	61.02	67.83

TABLE A3. OLS ESTIMATES OF THE EFFECT OF THE MIDDLE CLASS SCHOALRSHIP ON MALE AND FEMALE ENROLLMENTS

	(1)	(2)	(3)	(4)
	Male Students	Female Students	Male Students	Female Students
Effect of MCS	923.25	1215.19	711.91	1407.19
P Value	0.000	0.000	0.001	0.000
95% Confidence Interval	[740.62, 1105.88]	[944.70, 1485.68]	[275.26, 1148.55]	[715.63, 2098.76]
Observations	657	657	315	315
Year fixed effects	Yes	Yes	Yes	Yes
Institution fixed effects	Yes	Yes	Yes	Yes
Comparison Group	WICHE	WICHE	Bordering States	Bordering States

Notes: Estimates are based on annual data on institutions from 2011-2019 and obtained from the model described in equation (1). Columns 1 and 2 provide estimates for the effect of MCS on male and female enrollments respectively. Further, these estimates use eligible WICHE states as a counterfactual to the treatment group in California. These states include Arizona, Oregon, Alaska, Idaho, Montana, Utah, and Wyoming. Columns 3 and 4 provide estimates for the effect of MCS on female and enrollments respectively. These estimates use eligible bordering states as a counterfactual to the treatment group in California. These states include Arizona and Oregon.

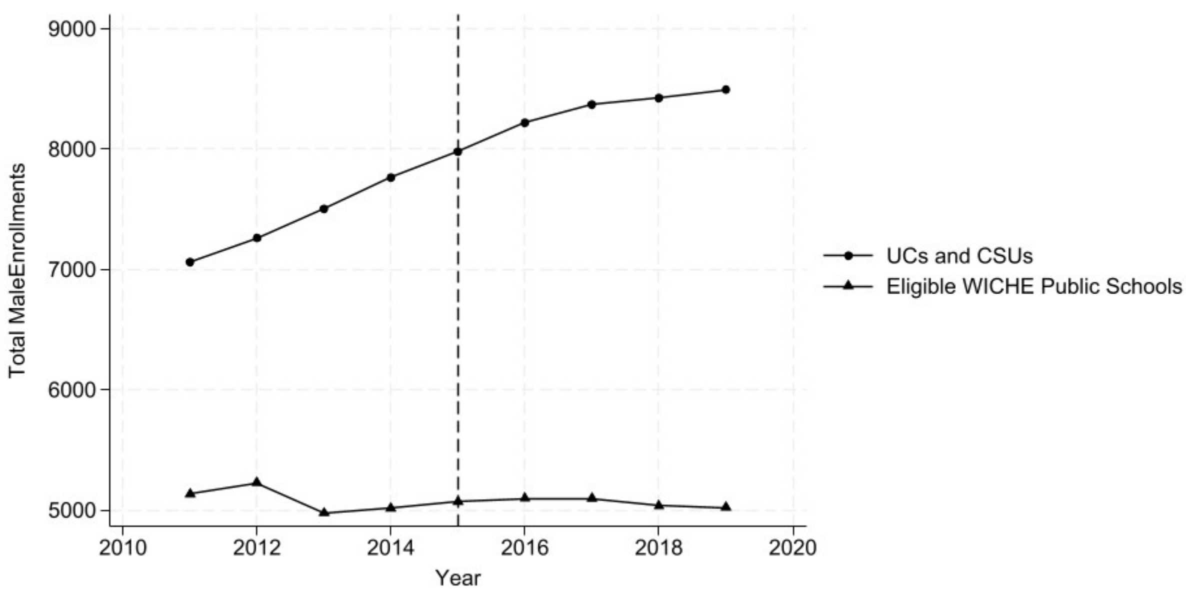


FIGURE A1. MALE ENROLLMENTS IN CALIFORNIA VS ELIGIBLE WICHE PUBLIC SCHOOLS

Notes: The vertical line, drawn at 2015 represents the year the need-based program was implemented.
Source: See Figure 1.

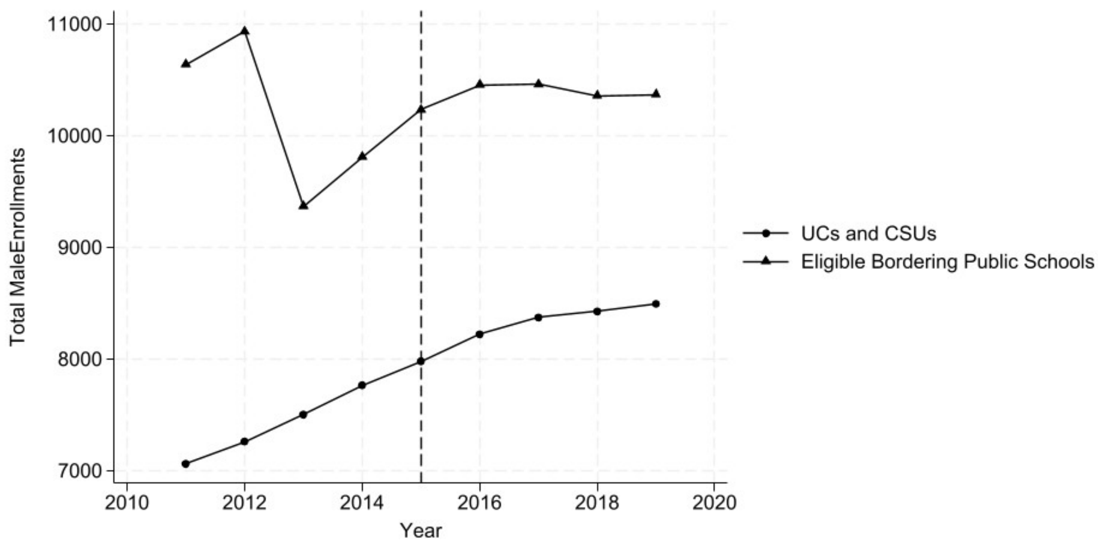


FIGURE A2. MALE ENROLLMENTS IN CALIFORNIA VS ELIGIBLE BORDERING STATE PUBLIC SCHOOLS

Notes: The vertical line, drawn at 2015 represents the year the need-based program was implemented.
Source: See Figure 1.

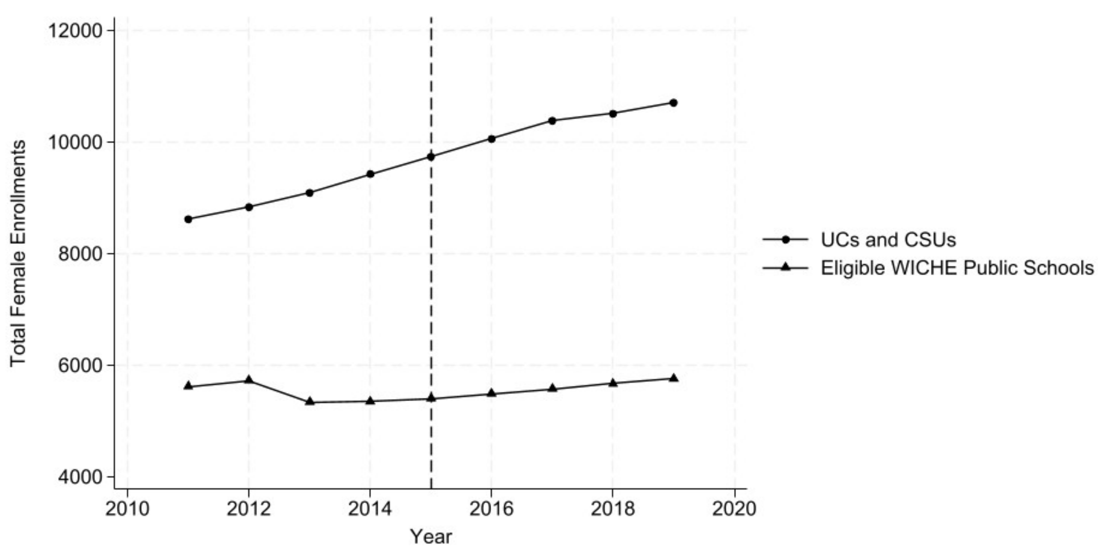


FIGURE A3. FEMALE ENROLLMENTS IN CALIFORNIA VS ELIGIBLE WICHE PUBLIC SCHOOLS

Notes: The vertical line, drawn at 2015 represents the year the need-based program was implemented.
Source: See Figure 1.

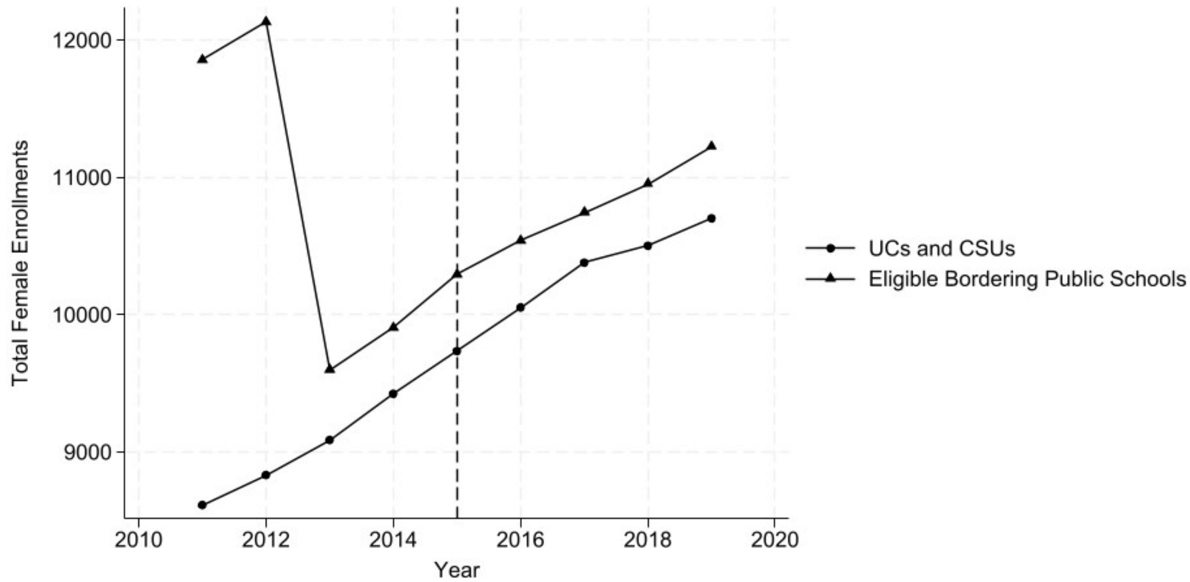


FIGURE A4. FEMALE ENROLLMENTS IN CALIFORNIA VS ELIGIBLE BORDERING STATE PUBLIC SCHOOLS

Notes: The vertical line, drawn at 2015 represents the year the need-based program was implemented.
Source: See Figure 1.

TABLE A4. OLS ESTIMATES OF THE EFFECT OF THE MIDDLE CLASS SCHOALRSHIP ON GRADUATION RATES

	(1)	(2)
Post*Treat	4.79	2.
P Value	0.000	0.000
95% Confidence Interval	[3.18, 6.39]	[1.51, 4.47]
Observations	612	350
Year fixed effects	Yes	Yes
Institution fixed effects	Yes	Yes
Comparison Group	Eligible WICHE states	Eligible Bordering states

Notes: Estimates are based on annual data on institutions from 2011-2019 and obtained from the model described in equation (1). Column 1 estimates use eligible WICHE states as a counterfactual to the treatment group in California. These states include Arizona, Oregon, Alaska, Idaho, Montana, Utah, and Wyoming. Column 2 estimates use eligible bordering states as a counterfactual to the treatment group in California. These states include Arizona and Oregon.

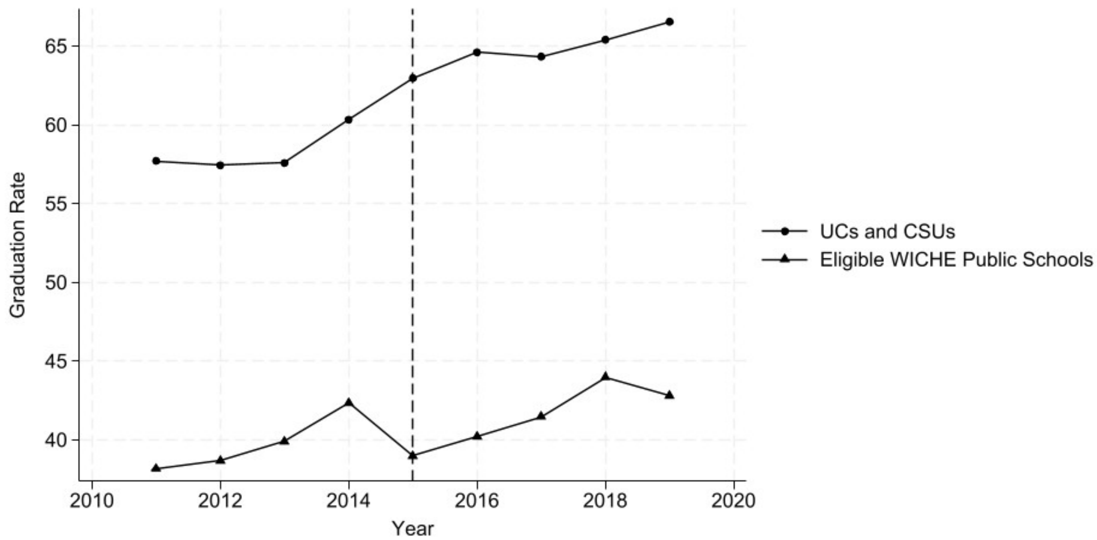


FIGURE A5. GRADUATION RATES IN CALIFORNIA VS OTHER ELIGIBLE WICHE STATES

Notes: The vertical line, drawn at 2016 represents the year the need-based program theoretically first began affecting graduation rates. Each circle dot represents the average total enrollments of the corresponding year for all California schools. Each triangle dot represents the average total enrollments of the corresponding year for all other eligible WICHE schools. The eligible WICHE includes Arizona, Oregon, Alaska, Idaho, Montana, Utah, and Wyoming

Source: Annual data on total enrollments by institution and year provided by the Integrated Post-Secondary Education System.

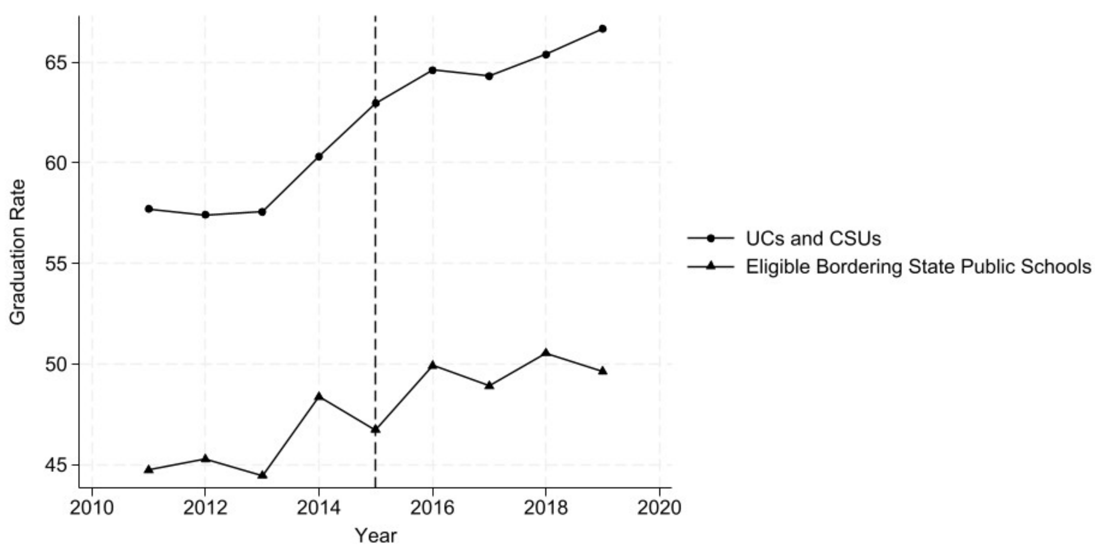


FIGURE A6. GRADUATION RATES IN CALIFORNIA VS OTHER ELIGIBLE BORDERING STATES

Notes: The vertical line, drawn at 2016 represents the year the need-based program theoretically first began affecting graduation rates. Each circle dot represents the average total enrollments of the corresponding year for all California schools. Each triangle dot represents the average total enrollments of the corresponding year for all other eligible bordering state schools. The eligible bordering states include Arizona and Oregon.

Source: Annual data on total enrollments by institution and year provided by the Integrated Post-Secondary Education System.

TABLE A5. OLS ESTIMATES OF THE EFFECT OF THE MIDDLE CLASS SCHOALRSHIP ON MALE AND FEMALE GRADUATION RATES

	(1)	(2)	(3)	(4)
	Male Students	Female Students	Male Students	Female Students
Effect of MCS	4.40	5.31	3.37	2.75
P Value	0.00	0.000	0.000	0.003
95% Confidence Interval	[2.55, 6.25]	[3.44, 7.19]	[1.67, 5.06]	[0.92, 4.59]
Observations	612	612	350	350
Year fixed effects	Yes	Yes	Yes	Yes
Institution fixed effects	Yes	Yes	Yes	Yes
Comparison Group	WICHE	WICHE	Bordering States	Bordering States

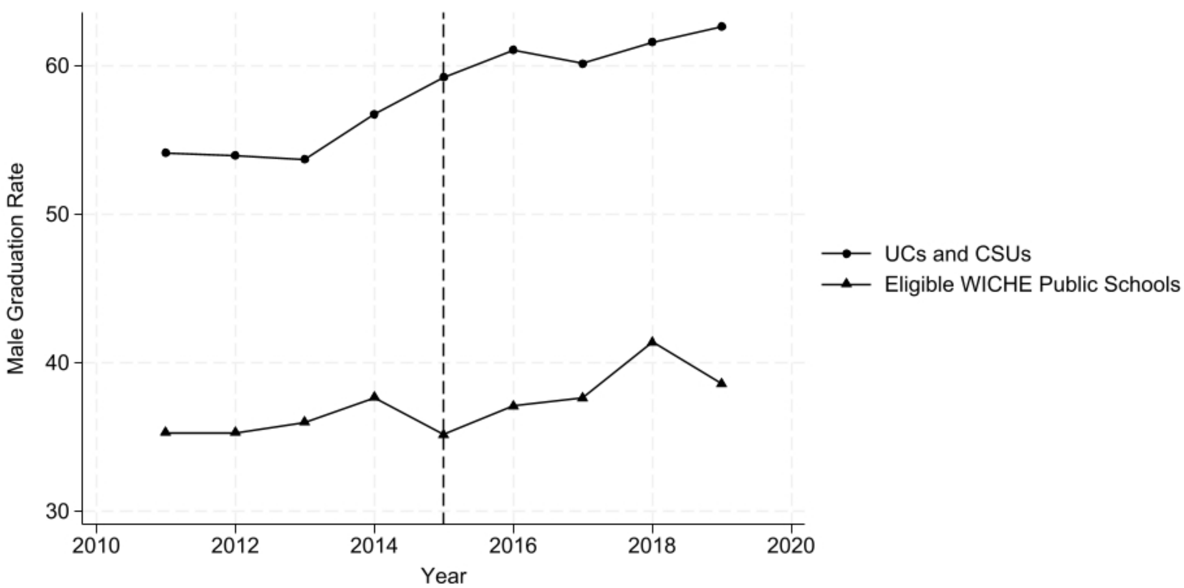


FIGURE A7. MALE GRADUATION RATES IN CALIFORNIA VS OTHER ELIGIBLE WICHE STATES

Notes: See Figure A5.
Source: Annual data on total enrollments by institution and year provided by the Integrated Post-Secondary Education System.

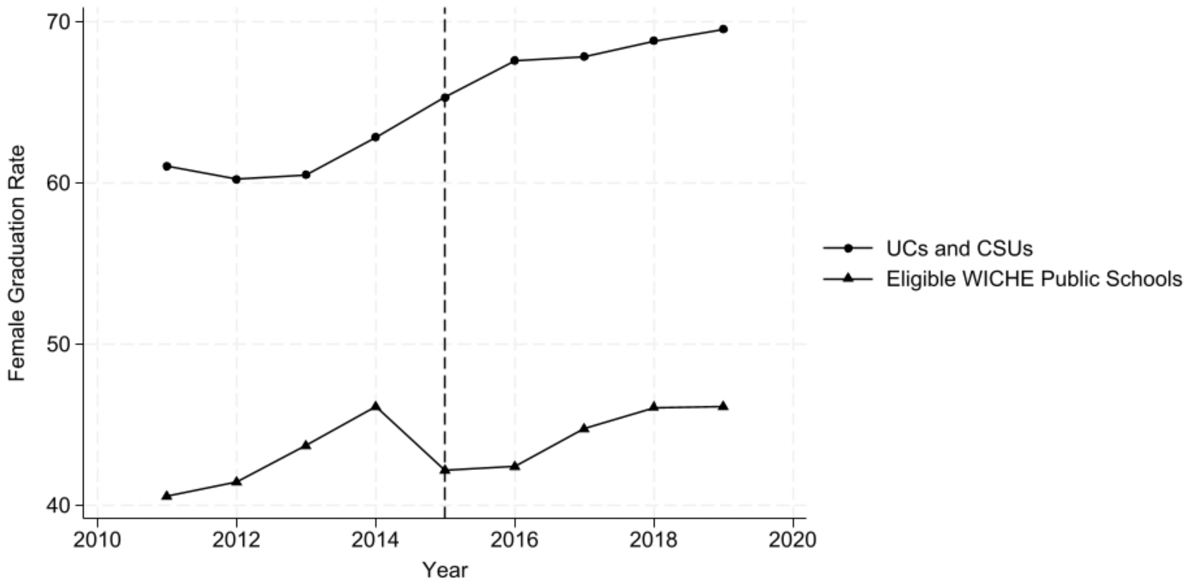


FIGURE A8. FEMALE GRADUATION RATES IN CALIFORNIA VS OTHER ELIGIBLE WICHE STATES

Notes: See Figure A5.
Source: Annual data on total enrollments by institution and year provided by the Integrated Post-Secondary Education System.

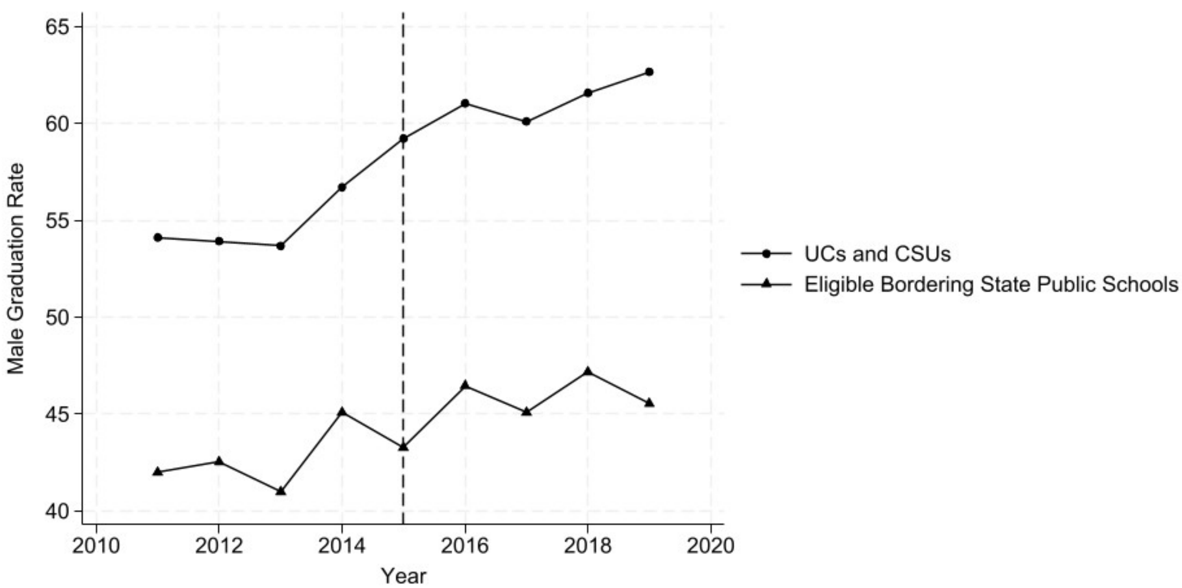


FIGURE A9. MALE GRADUATION RATES IN CALIFORNIA VS OTHER ELIGIBLE BORDERING STATES

Notes: See Figure A6.
Source: Annual data on total enrollments by institution and year provided by the Integrated Post-Secondary Education System.

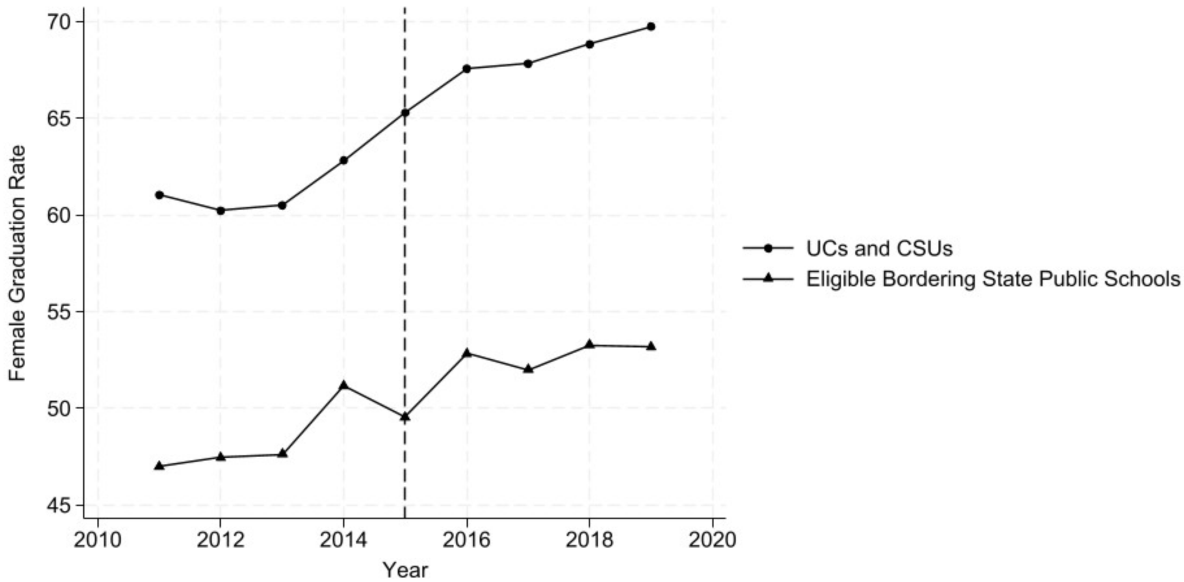
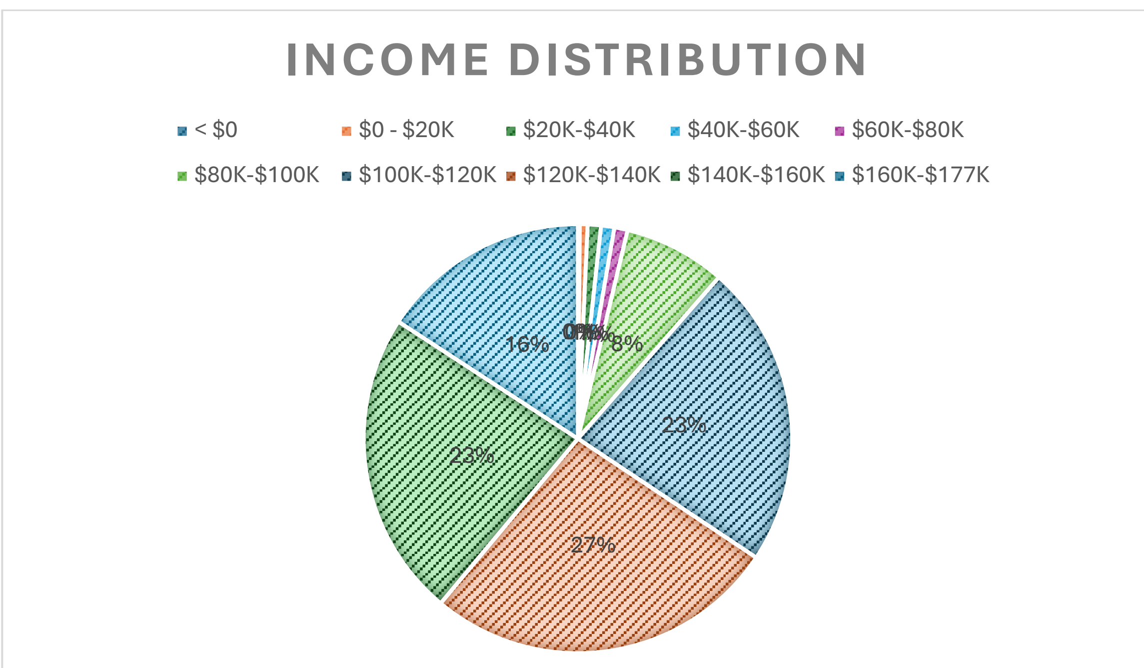


FIGURE A10. FEMALE GRADUATION RATES IN CALIFORNIA VS OTHER ELIGIBLE BORDERING STATES

Notes: See Figure A6.
Source: Annual data on total enrollments by institution and year provided by the Integrated Post-Secondary Education System

TABLE A6. INCOME DISTRIBUTION OF 2015 MCS RECIPIENTS



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