# Local Graduation Policies as a Tool for Increasing College Eligibility: Evidence from Los Angeles

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#### Abstract

Local school boards in California have been passing policies to increase their local math graduation requirements. Though proponents claim these policies would increase college readiness and student outcomes, others are concerned they may negatively impact students' ability to graduate. Little causal evidence exists regarding the effects of these district-level policies. Focusing on public school districts in Los Angeles County, I apply a generalized difference-in-difference model to show that the increase in graduation requirements yields a 7.2 percentage point increase in the completion of requirements necessary to apply for University of California and California State University schools and a 5.4 percentage point increase in graduation rates. However, the effect on California State University and University of California admission rates is insignificant.

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## 1 Introduction

Attending college has a significant positive impact on individuals' economic outcomes and that of their state, and there is an established body of literature that has described the growth in the college wage premium (Card, 1999; Hanushek and Woessmann, 2008). In addition, educational attainment explains a large proportion of the United States' racial differences in social and economic outcomes (Neal and Johnson, 1995). However, college enrollment rates for Black and Latino students is more than 10% lower than that of White students in California (Kurlaender et al., 2018). As such, policymakers and education administrators have sought to improve the college eligibility and readiness of underrepresented minorities. Furthermore, CSU and UC schools are some of the top colleges in the nations in terms of income mobility (Chetty et al., 2017). Therefore, effective interventions to help students gain admission to these campuses are of great interest to those who seek to address income inequality.

Following the 1983 A Nation at Risk Report that scrutinized the lack of rigor in United States coursework, California raised its math graduation requirements from zero to two courses. Previous literature attempted to model the causal effect of such state policies on educational attainment (Harvill, 2011; Goodman, 2019). However, the California's requirements remain below that of those to be admitted by a California State University (CSU) or a University of California (UC) campus. In particular, CSU and UC campuses require students to complete 3 years of math in order to be eligible for admission, while the California only requires 2 years to graduate. Some education administrators and district policymakers cite this difference in math requirements as the biggest barrier to student being eligible to apply for UC and CSU admission. Consequently, only 50.5% of California high school graduates in 2019 met the A-G course requirements, the minimum courses needed to be admitted by a UC or CSU school (CA Dept. of Education). With the intention of increasing student college eligibility and success, school districts have adopted more stringent local graduation requirements. According to surveys conducted by the Public Policy Institute of California, 51%

California school districts in 2017 required students to complete the A-G course sequence and 66% required at least a third year of math to graduate in 2019.

While most local school board policies to increase graduation requirements were passed without news coverage or public awareness, Los Angeles Unified School District's and Long Beach Unified School District's policies were extensively discussed by administrators, parents, and the education community. In 2010, LAUSD parents marched in a rally outside the LAUSD headquarters to promote the adoption of the A-G requirements as their district's own standard. In 2014, LBUSD voted to increase its math graduation requirement to 3 years starting 2018 and 4 years in 2019. Long Beach Unified Superintendent Christopher Steinhauser, who is also on the CSU board of trustees, attributes the 20 percentage point increase in his district's A-G completion rate to the increased math requirement. The district's success has been used as anecdotal evidence to support a proposal to increase the CSU math admissions requirement from 3 years to 4 years.

School districts, government entities, nonprofits, and researchers implement different policies and programs to try to increase college eligibility and enrollment. Existing papers have looked at the effects of interventions such as college student mentors, financial aid application assistance, information packets, and summer counseling (Carrell and Sacerdote, 2017; Bettinger et al., 2012; Hoxby et al., 2013; Castleman et al., 2014). Drawing upon data on school districts in Los Angeles County, this paper adds to this literature by inferring the causal effect of local school board policies that increase math graduation requirements on the district's graduation rate, UC admission, and CSU admission. Furthermore, I seek to model the extent to which the rise in A-G completion rates exhibited by districts such as LBUSD was actually caused by the implementation of local math graduation requirements.

Increased math requirements may induce positive economic and social outcomes by enhancing students' cognitive skills, increasing their college eligibility, or influencing their career choice (Aughinbaugh, 2012; Levine and Zimmerman, 1995; Joensen and Nielsen, 2009). Existing papers suggest that students who do take additional math coursework have a higher probability of going to college and earn higher wages. However, the requirements may instead be a barrier for students who are unable to meet the requirements and fail to graduate (Harvill, 2011; Plunk et al., 2014). Goodman (2019) does not find either of these effects when analyzing increases in math graduation requirements at the state level. However, district-level policies may be more effective in fostering state college admission than statewide policies because they may increase the achievement level of their students relative to those from districts with less stringent graduation requirements. Alternatively, district-level policies may be less effective because districts have less resources to implement the policy change than the state government. In this paper, I show that local school district policies that increase graduation requirements have a positive causal impact on students' eligibility to apply for CSU and UC schools, but not on their admission into these universities.

### 2 Literature Review

Existing literature on the effects of math graduation requirements focus on state-level policies implemented at different years since the 1983 A Nation at Risk Report. Teitelbaum (2003) utilized a multilevel regression model to analyzed sampled student data from the National Educational Longitudinal Study (NELS) conducted in 1988 and found that state's threecourse requirements in math and science is associated with students earning more credits in math and science. However, Teitelbaum also found evidence that many schools had not strictly enforced these new graduation requirements.

Harvill (2011) developed a dynamic discrete choice model to analyze data from NELS:88/2000 to analyze the impact of states implementing policies that require students to complete Algebra, Geometry, and Algebra II. Harvill's model simulations show that educational attainment at age 18 is responsive to the policy change, but found that the policies are associated with a fall in on-time high school graduation rate.

Joensen and Nielsen (2009) exploited a high school pilot scheme in Denmark to identify

the causal effect of high school math coursework on labor market outcomes and found a 20% earnings increase due to advanced math curriculum.

Aughinbaugh (2012) applied a household fixed effect model to analyze student data from NLSY97 to estimate the effect of high school math curriculum on student outcome and found that students who take advanced math courses in high school are more likely to start college.

Plank et. al (2014) used logistic regression to model the effects of math and science graduation requirements on student outcomes and found an association between increased graduation requirements and higher dropout rates. However, the authors do not extensively account for selection bias.

Goodman (2019) used a difference-in-difference framework with state and cohort fixed effects to analyze sampled transcript and Census data, finding that state reforms increased the number of math classes that Black high school students took. However, Goodman did not find a significant effect of the state policies on educational attainment.

Districts that already have more stringent graduation requirements may not be affected by the timing of state requirement changes. Though previous studies attempt to exploit differences in state math requirement policies to analyze the effects of math coursework, they do not account for differences in local graduation requirements. For example, Goodman (2019) does not include district fixed effects or cluster standard errors by school district.

While Gao (2021) does attempt to find the effects of district-level requirements in California on student outcomes, their OLS model can only partially account for selection bias and they only find an association between districts with higher math high school graduation requirements and higher A-G completion rate. This paper extends this analysis by exploiting panel data on school districts in Los Angeles County to find the policies' causal effect.

### 3 Data

Data on high school graduation requirements for school districts in Los Angeles County was collected from each district's website. To identify whether and when these requirements changed in the past ten years, I reviewed their historical school board policies and meeting agendas. Since most districts did not post their policies and agenda prior to 2010. I assumed that school districts that only require two years of math did not change their math requirement policies since that is the state's minimum.

 Table 1: Los Angeles County Graduation Requirement Changes

Year	Grad. Req. Change
2024	+1 year ethnic studies
2022	+1 year math, $+$ all A-G in 2024
2021	+1 year math
2020	+0.5 year ethnic studies
2019	+1 year math
2018	+1 year english
2018	+2 year math (+1 in 2018, +1 in 2019)
2016	+1 year math, $+2$ years world language
2016	+1 year math
2016	-1 year english (repealed 2017)
2014	+1 year math, $+1$ year world language
2012	+1 year science (repealed)
2011	-0.5 years geography, -0.5 years $*CTE$
2011	+1 year math, $+1$ year world language
2010	-1 year social science
2008	+1 year science
	2024 2022 2021 2020 2019 2018 2018 2016 2016 2016 2016 2014 2012 2011 2011 2010

Note: Year based on first graduating cohort year that the policy affects. \*Career Technical Education.

The year listed in Table 1 is the year of the first graduating cohort which the requirement officially applies to. However, many of these policies were passed at least three years prior so that the change does not impact students who started high school before the policy was changed and give schools time to implement the policy. For my analysis, I focused on school districts that enacted increased math graduation requirements. Though one of the districts implements a 4th year of English as a requirement starting in 2018, almost all the other districts had already required 4 years of English since before 2010.

Data on school districts including number of high school graduates, the number of students who complete the A-G requirements, free or reduced lunch rates, percentage English learners, high school enrollment by race, and expenditure per student come from the California Department of Education Student & School Data Files. The data spans 2010 to 2020 and each school has an identifying county-district-school (CDS) code.

Data on CSU admission and application spanning from 2000 to 2020 comes from the California State University Enrollment Dashboard. The dashboard lists the number of applicants, admits, and enrollees by California high school. The data is also disaggregated by race and gender. For my analysis, I first took a subset of the data that only includes public schools in Los Angeles. I filled in missing values based on the value of the previous year for the school if available. I aggregated the data by district by using the first 7 numbers of the CDS code, which uniquely identifies each district in California.

Data on UC admission and application comes from the UC System Infocenter. The data is available by high school in California by year spanning from 1994 to 2020. The data can be disaggregated by race and gender. However, values for high schools with less than 5 applicants of a particular race are suppressed. In addition, each school is identified by its College Entrance Examination Board. I merged the data with the NCES/CEEB Code Crosswalk developed by Mark Davenport. Then, I aggregated the data by the first 7 numbers of the CDS code and merged it with the CSU and CDE data. The resulting data spans 2010 to 2020 and has 559 observations.

To account for differences in the size of districts and make the dependent variable more interpretatable, I divided the student counts by the number of students in the district's cohort then multiplied the result by 100. The variables of interest range from 0 to 100 and are the percentage of high school seniors who complete the UC/CSU A-G requirements (Complete A-G), who graduate (Graduate), the percentage of high school seniors who are admitted by a CSU school (CSU Admit), the percentage of students who are admitted by a UC school (UC Admit), the percentage of high school seniors who are apply to a CSU school (CSU App), and the percentage of students who apply to a UC school (UC App).

Due to disruptions caused by the coronavirus pandemic, many districts eased graduation requirements to different degrees for the class of 2020. Therefore, I exclude 2020 in my analysis. As a result, William S. Hart Union High School District lacks data post policy implementation. As a result, the 5 relevant school districts in my treatment group are Los Angeles Unified, Long Beach Unified, Azusa Unified, Beverly Hills Unified, and Culver City Unified School Districts. For my control group, I found 27 school districts in Los Angeles County that has not required additional math beyond the 2 years required by the state. At the district level, my treatment to control ratio is 5:27. However, there are actually more students in the 5 treatment districts than the 27 control districts because Los Angeles Unified is the largest school district in California. On average, the annual student cohort size of the treatment group is 49,726 while the cohort size of the control group is 29,907 students.

Statistic	Ν	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
CSU Applicants	51	928	3,008	107	249	693	21,794
CSU Admits	51	671	2,067	66	195	513	14,967
UC Applicants	51	465	1,236	44	144	428	8,983
UC Admits	51	301	747	27	94	285	5,420
Complete A-G	51	844	2,189	111	272	671	15,856
Graduates	51	1,772	4,228	267	587	$1,\!474$	30,557
Cohort Size	51	$2,\!179$	5,760	284	626	1,785	41,633

 Table 2: Summary Statistics

Note: 10-year average at district aggregate level. CSU data from CSU Enrollment Dashboard. UC Data from UC System Infocenter. A-G completion, number graduates, and cohort size data from California Department of Education.

Table 3 describes average characteristics for the Control Group and Treatment Group. Overall, the Treatment Group has more low-income students, more Hispanic/Latino students, lower median family income, and more students who score below proficient on Math and English standardized exams.

	Control Group	Treatment Group
Number of Districts	27	5
Percent Graduate	87.35	86.38
Percent English Learners	14.28	18.70
Percent Meet or Exceed ELA Std.	44.66	32.78
Percent Meet or Exceed Math Std.	44.66	32.78
Median Family Income	98,974.31	89,565.20
Average Expend. Per Student	10,346.34	12, 136.35
Percent Free or Reduced Lunch	43.21	54.12
Percent Black	5.03	8.77
Percent American Indian/Alaska Native	0.27	0.26
Percent Asian	19.73	7.14
Percent Filipino	2.60	1.83
Percent Hispanic/Latino	42.77	53.40
Percent Multiracial	3.39	2.28
Percent Pacific Islander	0.29	0.52
Percent White	24.97	25.20

 Table 3: Balance Table

## 4 Empirical Approach

To model the causal effect of district-level math graduation requirement policies with districts that changed their policies during different years, I exploit a difference-in-difference framework with district and year fixed effects. The first model I estimated was the following:

$$Y_{i,t} = \bar{\alpha}_0 + \delta_t + \gamma_i + \theta(PostTreat_{i,t} \times TreatDistrict_i) + \epsilon_{i,t}$$
(1)

For district *i* and year *t*,  $Y_{i,t}$  is the variable of interest,  $\delta_t$  are year specific intercepts,  $\gamma_i$  are district specific intercepts,  $(PostTreat_t \times TreatDistrict_i)$  is the interaction between an indicator variable identifying post treatment year and an indicator for the treatment group.  $\theta$  is the estimate for the causal effect of requirement policy implementation on the dependent variable  $Y_{i,t}$ .

To check for the parallel trends assumption, I graphed the trends in the dependent variables across time for each of the treatment districts along with the control group's average across time. These graphs are included as Figures 2-5 in the Appendix. Beverly Hills Unified only has one pre-implementation year available in the data since their policy came into effect in 2011. For the UC A-G requirement completion rates graphs, Los Angeles Unified School district exhibited a steeper positive pre-trend than the control group. This may be due to the district requiring all its students to enroll in A-G courses starting with the class of 2012.

The two-way fixed effects difference-in-difference model is a quasi-experimental model that Goodman-Bacon (2018) shows is a weighted average of all possible two-group/twoperiod difference-in-difference estimators. A potential issue with this model is that timing and choice to implement the requirement may be correlated with omitted variables that vary across time and district. I attempt to account for this bias by analyzing a generalized two-way fixed effects difference-in-difference model:

$$Y_{i,t} = \bar{\alpha}_0 + \delta_t + \gamma_i + z'_{it}\beta + \theta(PostTreat_t \times TreatDistrict_i) + \epsilon_{i,t}$$
(2)

 $z'_{it}$  is the vector of control variables that includes race variables, percent English learners, percent of students with free or reduced lunch, and general fund expenditure per student.

As a robustness check and to visualize the variation in the treatment effect across time, I also estimate a model with leads and lags running 3 years before policy implementation and two years after (Autor, 2003; Angrist and Pischke, 2008). This is to check that the effect occurs after policy implementation and not before. We may see the effects of the policy before the first year it comes into effect because some districts may have implemented changes that affect the dependent variable leading up to the start of the policy. The equation that I model to check for this is the following:

$$Y_{i,t} = \bar{\alpha}_0 + \delta_t + \gamma_i + z'_{it}\beta + \sum_{k=-3}^{k=+2} \theta_k[t = \tau_i + k] + \epsilon_{i,t}$$

$$\tag{3}$$

We let  $\tau_i$  be the period at which district *i* is treated and we let *k* be the number of years before or after  $tau_i$ . The results are visualized in Figure 1 in the Appendix.

### 5 Results and Discussion

Table 4 and 5 summarize the results of the two-effects difference-in-difference models. In this specification, we see that the interaction term identifying treatment year and district has a positive coefficient representing an 8.879 percentage point increase in students in the district who complete the A-G requirements. In addition, the model shows that graduation rate increases by 6.825 percentage points due to the implementation of the increased math graduation requirement. Both of these values are statistically significant with p-values below 0.1. We also see a 3.716 percentage point increase in Hispanic and Latino students admitted by a CSU school that is statistically significant with p-value below 0.05. However, this result does not hold up in the generalized difference-in-difference model. Furthermore, we do not see a causal effect of the district requirements on overall UC/CSU admission rates or on UC/CSU application rates.

These results suggest that some students who were otherwise not going to complete the A-G requirements did rise to the occasion when the district required additional requirements that better aligned their local requirements with those set by UC and CSU schools. However, this may not enough to actually impact the percentage of students who actually apply and are admitted to these schools because there may be other financial or social barriers that prevent students from pursuing college despite their eligibility.

Table 6 and 7 summarizes the results of the generalized two-effects difference-in-difference model. Though the magnitude of difference-in-difference estimator decreases in magnitude, the coefficients are still statistically significant for the A-G completion rate and graduate rate. The model shows that implementing the district math requirement policy yields a 7.169 percentage point increase in the proportion of students who complete the UC/CSU A-G course requirements. The lead and lag variable coefficients for the model I ran to test the robustness of the result exhibit consistent values for the lag variables and increasing values for the lag variables. This suggests that the impact of the policy may be greater 1 and 2 years after the policy was implemented. Surprisingly, the policy does not have a negative effect on graduation rates as previous literature finds at the state level. In fact, I find that the policies yield a 5.357 percentage point increase in the district's graduation rate. However, the coefficients for the lag variables (See Equation 3 and Appendix Figure 1) are not steady and might suggest that this estimate is biased.

Table 4: Diff-in-Diff Models with Time and District Fixed Effects

	Dependent variable:					
	Complete A-G	Graduate	CSU Admit	UC Admit	CSU App	UC App
	(1)	(2)	(3)	(4)	(5)	(6)
TreatedDistrict  imes PostTreat	$8.879^{***}$ (3.091)	$6.825^{***}$ (1.694)	$0.286 \\ (1.479)$	1.743 (1.068)	-0.245 (1.892)	$2.255^{*}$ (1.188)
Observations	306	309	309	309	309	309
$\mathbb{R}^2$	0.815	0.748	0.760	0.951	0.715	0.961
Adjusted R <sup>2</sup>	0.787	0.710	0.724	0.944	0.673	0.955
Residual Std. Error	8.896 (df = 265)	4.880 (df = 268)	4.262 (df = 268)	3.077 (df=268)	5.450 (df = 268)	3.423 (df=268

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### Table 5: Diff-in-Diff Models with Time and District Fixed Effects, Latino & Black

	Dependent variable:						
	Latino CSU Admit	Latino UC Admit	Black CSU Admit	Black UC Admit			
	(1)	(2)	(3)	(4)			
TreatedDistrict  imes PostTreat	$3.716^{**}$ (1.718)	0.869 (1.515)	0.285 (1.405)	1.371 (2.648)			
Observations	288	309	50	239			
$\mathbb{R}^2$	0.843	0.836	0.914	0.769			
Adjusted R <sup>2</sup>	0.819	0.811	0.879	0.728			
Residual Std. Error	4.498 (df = 249)	4.365 (df = 268)	2.561 (df = 35)	6.696 (df = 202)			

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Complete A-G (1)	Graduate	CSU Admit	UC Admit	0077	
	( <b>0</b> )		UC Admit	CSU App	UC App
7 1 60**	(2)	(3)	(4)	(5)	(6)
$7.169^{**}$ (3.478)	$5.357^{***}$ (1.714)	0.823 (1.529)	0.343 (1.062)	1.434 (1.973)	$2.042^{*}$ (1.225)
-0.926 (0.871)	-0.522 (0.426)	$-1.057^{***}$ (0.380)	$-0.862^{***}$ (0.264)	$-0.951^{*}$ (0.490)	$-0.532^{*}$ (0.304)
$\begin{array}{c} 0.410 \\ (0.348) \end{array}$	$0.446^{***}$ (0.170)	$\begin{array}{c} 0.522^{***} \\ (0.151) \end{array}$	$\begin{array}{c} 0.472^{***} \\ (0.105) \end{array}$	$\begin{array}{c} 0.477^{**} \\ (0.195) \end{array}$	$0.265^{**}$ (0.121)
-1.903 (5.198)	$-10.783^{***}$ (2.541)	$-5.595^{**}$ (2.267)	$-4.343^{***}$ (1.575)	$-7.272^{**}$ (2.925)	$-6.840^{***}$ (1.816)
$0.601 \\ (0.701)$	-0.291 (0.342)	$0.189 \\ (0.305)$	-0.185 (0.212)	$\begin{array}{c} 0.277 \\ (0.394) \end{array}$	-0.335 (0.245)
1.167 (2.659)	$2.463^{*}$ (1.264)	$2.500^{**}$ (1.128)	-0.230 (0.783)	$3.499^{**}$ (1.455)	$1.376 \\ (0.904)$
$0.847^{*}$ (0.445)	$0.726^{***}$ (0.218)	$0.703^{***}$ (0.194)	$\begin{array}{c} 0.741^{***} \\ (0.135) \end{array}$	$0.650^{***}$ (0.250)	$\begin{array}{c} 0.493^{***} \\ (0.155) \end{array}$
$0.367 \\ (0.390)$	0.078 (0.187)	$0.078 \\ (0.167)$	-0.031 (0.116)	$0.143 \\ (0.215)$	$\begin{array}{c} 0.173 \\ (0.134) \end{array}$
$0.212 \\ (0.205)$	$0.176^{*}$ (0.100)	$0.107 \\ (0.089)$	0.047 (0.062)	$0.166 \\ (0.115)$	-0.015 (0.072)
$0.0002 \\ (0.001)$	$-0.002^{***}$ (0.001)	$-0.002^{***}$ (0.0005)	$-0.001^{**}$ (0.0003)	$-0.002^{***}$ (0.001)	$-0.001^{**}$ (0.0004)
$306 \\ 0.819 \\ 0.784$	309 0.800 0.762	309 0.801 0.763	309 0.963 0.956	309 0.760 0.715	$     309 \\     0.968 \\     0.962 \\     3.160 (df=25) $
	$\begin{array}{c} -0.926\\ (0.871)\\ 0.410\\ (0.348)\\ -1.903\\ (5.198)\\ 0.601\\ (0.701)\\ 1.167\\ (2.659)\\ 0.847^*\\ (0.445)\\ 0.367\\ (0.390)\\ 0.212\\ (0.205)\\ 0.0002\\ (0.001)\\ \hline \end{array}$	$\begin{array}{cccc} -0.926 & -0.522 \\ (0.871) & (0.426) \\ \hline 0.410 & 0.446^{***} \\ (0.348) & (0.170) \\ -1.903 & -10.783^{***} \\ (5.198) & (2.541) \\ \hline 0.601 & -0.291 \\ (0.701) & (0.342) \\ \hline 1.167 & 2.463^{*} \\ (2.659) & (1.264) \\ \hline 0.847^{*} & 0.726^{***} \\ (0.445) & (0.218) \\ \hline 0.367 & 0.078 \\ (0.390) & (0.187) \\ \hline 0.212 & 0.176^{*} \\ (0.205) & (0.100) \\ \hline 0.0002 & -0.002^{***} \\ (0.001) & (0.001) \\ \hline \end{array}$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{c ccccc} -0.926 & -0.522 & -1.057^{***} & -0.862^{***} & -0.951^{*} \\ (0.871) & (0.426) & (0.380) & (0.264) & (0.490) \\ \hline 0.410 & 0.446^{***} & 0.522^{***} & 0.472^{***} & 0.477^{**} \\ (0.348) & (0.170) & (0.151) & (0.105) & (0.195) \\ \hline -1.903 & -10.783^{***} & -5.595^{**} & -4.343^{***} & -7.272^{**} \\ (5.198) & (2.541) & (2.267) & (1.575) & (2.925) \\ \hline 0.601 & -0.291 & 0.189 & -0.185 & 0.277 \\ (0.701) & (0.342) & (0.305) & (0.212) & (0.394) \\ \hline 1.167 & 2.463^{*} & 2.500^{**} & -0.230 & 3.499^{**} \\ (2.659) & (1.264) & (1.128) & (0.783) & (1.455) \\ \hline 0.847^{*} & 0.726^{***} & 0.703^{***} & 0.741^{***} & 0.650^{***} \\ (0.445) & (0.218) & (0.194) & (0.135) & (0.250) \\ \hline 0.367 & 0.078 & 0.078 & -0.031 & 0.143 \\ (0.390) & (0.187) & (0.167) & (0.116) & (0.215) \\ \hline 0.212 & 0.176^{*} & 0.107 & 0.047 & 0.166 \\ (0.205) & (0.100) & (0.089) & (0.062) & (0.115) \\ \hline 0.0002 & -0.002^{***} & -0.002^{***} & -0.001^{**} & -0.002^{***} \\ (0.001) & (0.001) & (0.005) & (0.0003) & (0.001) \\ \hline \end{array}$

### Table 6: Generalized Diff-in-Diff Models with Time and District Fixed Effects

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

	Dependent variable:					
	Latino CSU Admit	Latino UC Admit	Black CSU Admit	Black UC Admit		
	(1)	(2)	(3)	(4)		
TreatedDistrict  imes PostTreat	$0.266 \\ (1.749)$	1.473 (1.679)	-1.783 (1.612)	-2.543 (3.084)		
% Black	$-1.461^{***}$ (0.425)	-0.551 (0.417)	-1.259 (1.057)	$-2.369^{***}$ (0.753)		
% Hispanic or Latino	$\begin{array}{c} 0.632^{***} \\ (0.172) \end{array}$	$0.255 \\ (0.166)$	$1.166^{**}$ (0.525)	$1.017^{***}$ (0.334)		
% Native American or Alaskan	-2.865 (2.477)	-2.730 (2.489)	$1.659 \\ (4.812)$	7.929 (4.886)		
% Asian	-0.200 (0.346)	$0.256 \\ (0.335)$	$-6.418^{***}$ (2.217)	-0.875 (0.842)		
% Filipino	1.323 (1.256)	$0.422 \\ (1.238)$	$3.198 \\ (3.932)$	-0.912 (2.051)		
% White	$0.899^{***}$ (0.218)	$0.515^{**}$ (0.213)	$0.218 \\ (0.755)$	$0.920^{**}$ (0.419)		
% English Learners	$-0.386^{*}$ (0.200)	$0.069 \\ (0.183)$	$-0.659^{**}$ (0.297)	-0.499 (0.358)		
% Free or Reduced Lunch	$0.175^{*}$ (0.101)	-0.002 (0.098)	$-0.433^{**}$ (0.180)	$0.186 \\ (0.178)$		
Expenditure Per Student	0.0003 (0.001)	-0.0002 (0.0005)	-0.0005 (0.001)	-0.001 (0.001)		
Observations R <sup>2</sup> Adjusted R <sup>2</sup> Residual Std. Error	$288 \\ 0.864 \\ 0.837 \\ 4.263 (df=240)$	$\begin{array}{r} 309 \\ 0.844 \\ 0.814 \\ 4.331 \ (df{=}259) \end{array}$	$50 \\ 0.958 \\ 0.921 \\ 2.070 (df=26)$	$239 \\ 0.789 \\ 0.740 \\ 6.541 (df=193)$		

### Table 7: Diff-in-Diff Models with Time and District Fixed Effects, Latino & Black

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## 6 Conclusion

In this paper, I apply a quasi-experimental approach to determining the causal effect of district-level increases in math graduation requirements on the percentage of students who complete the UC/CSU A-G requirements, on graduation rates, and on UC/CSU admission. The generalized difference-in-difference model which controls for race, percent of students with free or reduced lunch, percent of students who are English learners, and expenditure per student show that the policies have a positive causal effect of 7.169 percentage points on the rates of students who complete the A-G requirements. In addition, I do not find a negative effect on graduation rates due to the policy. Future studies may seek to extend the analyses in this paper by applying matching, extending the analysis to all districts in California, applying synthetic control methods, or applying bootstrapping to estimate the standard error of the difference-in-difference coefficient.

Since students need to complete the UC/CSU A-G requirements in order to be admitted to a UC or CSU campus, these results show that the increase in district math requirements has a positive causal impact on college eligibility. However, even though these policies produce more students who are eligible to apply, the policies do not appear to have a significant effect on the percentage of students who are actually admitted by a CSU or UC campus. This may be due to students not applying to these schools even though more of them are eligible. In our model, we see that the increase in district math requirement does not have a significant effect on the rates of students applying to UC or CSU. Furthermore, students who were induced to become eligible may less likely be competitive applicants. However, the completion of these additional course may still have positive labor market effects as Goodman (2019) finds.

These results suggest that increasing district-level math graduation requirements can be effective in improving the rates of students who are eligible to apply for CSU and UC schools and that these requirements do not significantly reduce graduation rates. However, these policies are only a first step if district administrators seek to improve admission rates.

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# 7 Appendix: Tables and Figures

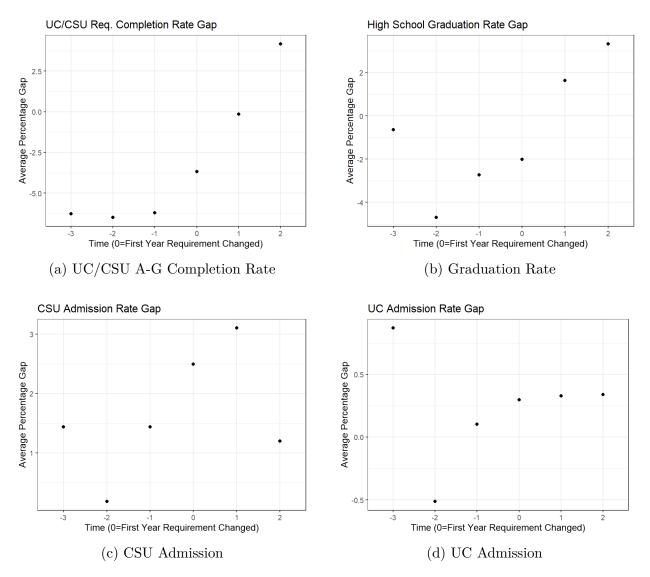


Figure 1: Lag and Lead Variable Coefficients: Estimated Impact of Increased Math Requirement

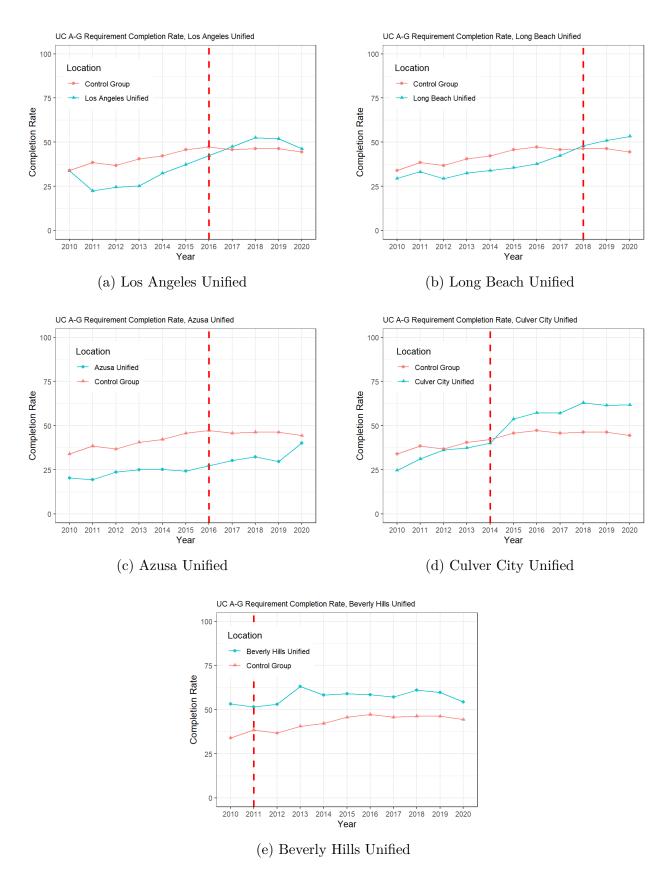
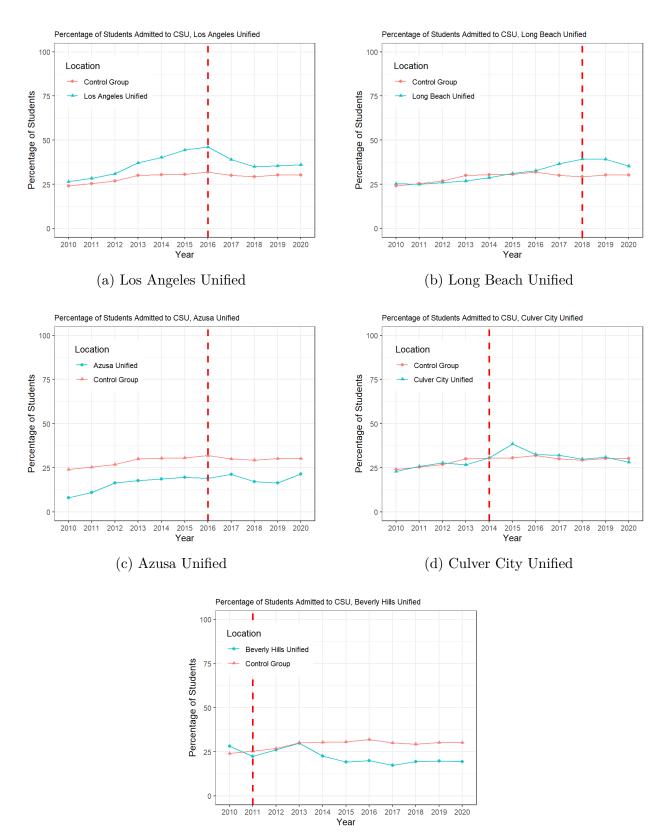


Figure 2: Percent of Student Cohort that Complete the UC/CSU A-G Course Requirements



(e) Beverly Hills Unified

Figure 3: Percent of Student Cohort Admitted by a Cal State University

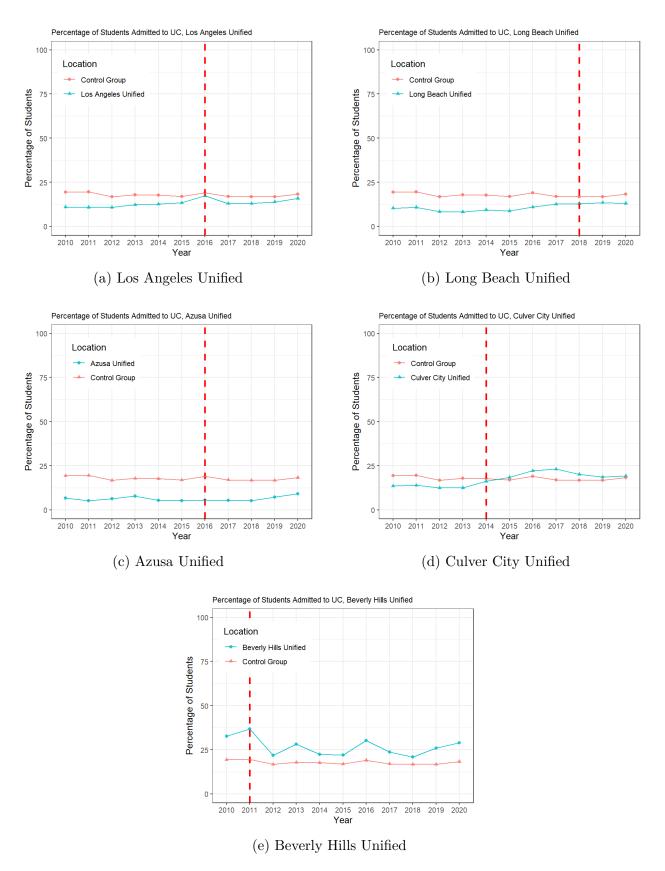


Figure 4: Percent of Student Cohort Admitted by a University of California school

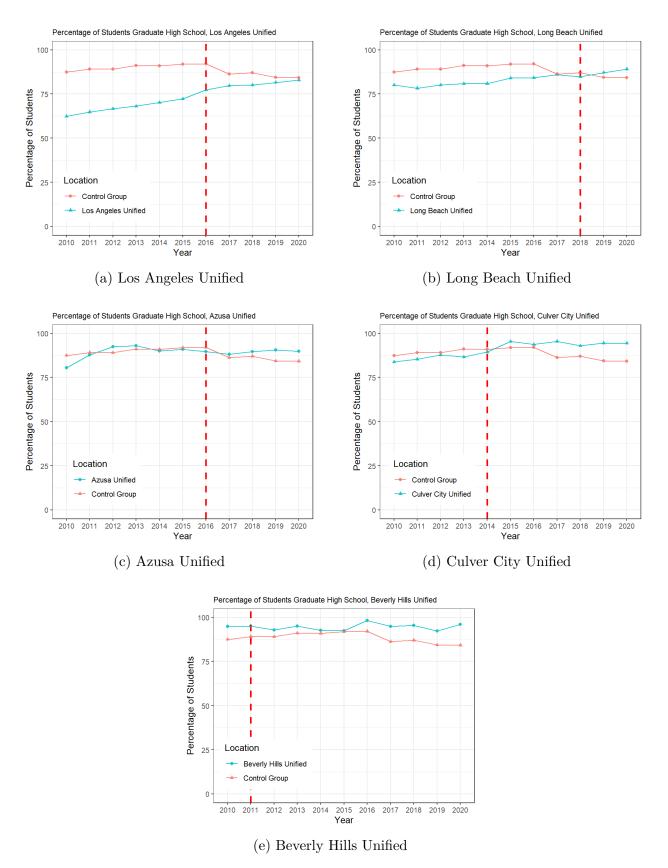


Figure 5: Cohort Graduation Rate