Does Banning Affirmative Action Hurt Racial Diversity? Evidence From U.S. Universities

By

PARK, Youjeong

THESIS

Submitted to

KDI School of Public Policy and Management

In Partial Fulfillment of the Requirements

For the Degree of

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Committee in charge:

Professor Yoon, Chungeun, Supervisor ____________________

Professor Rhee, Inbok ____________________

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Abstract

Affirmative action in U.S. university admissions aims to enhance student racial diversity and address educational inequities. However, 11 states have banned affirmative action in university admissions. This study examines the effects of these bans on student racial diversity across U.S. public universities from 1990 to 2020. I find that banning affirmative action has reduced undergraduate racial diversity. Specifically, there is a sharp rise in Hispanic enrollment shares while Asian, Black, and White enrollment shares remain unchanged. Furthermore, the study explores how state legislature partisanship creates variations in policy effects, showing that Asian enrollment shares have decreased in Democratic-led states. The results provide U.S. higher education policy implications on the interactions among affirmative action bans, student racial diversity, and state political factors.

Keywords: affirmative action, racial diversity, state legislature partisanship, U.S. higher education

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I. Introduction

Why is racial diversity vital in higher education? Student racial diversity on campus is crucial for shaping political identities, fostering acceptance of immigrants, and promoting college quality and academic performance (Akhtari et al., 2024). Race-based affirmative action policies in U.S. higher education aim to enhance student racial diversity and eliminate discrimination against under-represented students. However, starting in Texas in 1997, 11 states banned affirmative action in public university admissions. Affirmative action has been contentious regarding whether it increases racial diversity, as its bans shifted under-represented students' racial compositions (Arcidiacono et al., 2015). This paper examines the effects of banning affirmative action in U.S. higher education on student racial diversity from 1990 to 2020, given the importance of boosting student racial diversity for educational equity.

Post-ban changes in the student racial compositions across public universities bring the first research question. How have affirmative action bans changed student racial diversity over the period? Although earlier literature explores post-ban changes in Black or Hispanic enrollments and racial segregation between Black or Hispanic and White, little is known about the effects of affirmative action bans on student racial diversity (Hinrichs, 2020). Measuring pre- and post-ban differences in racial enrollment shares reveals how racial composition shifts affect student racial diversity. The analyses also show distinct effects of affirmative action bans on student racial diversity and racial enrollment shares across 11 states from 1990 to 2020.

The statewide differences in the effects of such bans address how state political factors vary policy effects, providing the second research question. How has state legislature partisanship created variations in the effects of affirmative action bans? The second research question is essential for finding mechanisms of variations in state policy effects within the U.S. context. State legislature partisanship creates variations in policy effects across the U.S.

because the implementations of liberal policies, such as affirmative action, are highly affected by the partisanship of state governments and their policy responsiveness (Caughey et al., 2017; Lax & Phillips, 2012). This study finds how state legislature partisanship shapes diverse statewide effects of such bans on student racial diversity and racial enrollment shares.

A dataset collected from 1990 to 2020 from the Integrated Postsecondary Education Data System, American Community Survey, U.S. Census, and National Conference of State Legislatures is used for the analyses. The dataset provides dependent variables of interest: the racial diversity measure and racial enrollment shares of Asian, Black, Hispanic, and White undergraduates. Moreover, the collection of observations yields a wide range of independent and control variables for each state and year: timing of affirmative action bans, racial compositions of pre-college demographics, and state legislative control.

This paper applies staggered difference-in-differences models to answer those research questions. The dataset from 1990 to 2020 allows the use of difference-in-differences to compare public universities' student racial diversity in 11 states that banned affirmative action versus those that did not before and after such bans. The period from 1990 to 1996 serves as a baseline to control for initial racial composition differences. This study particularly adopts staggered difference-in-differences models to estimate the dynamic effects of such bans over the period, considering heterogeneous treatment effects from different timings of banning affirmative action in public university admissions across 11 states. The empirical models also include an ethno-linguistic-fractionalization-based racial diversity measure that calculates the annual racial diversity of undergraduates in each university for Asian, Black, Hispanic, and White students.

The results reveal the effects of affirmative action bans on student racial diversity and racial enrollment shares, including its differences by state legislative control. Affirmative action bans have significantly reduced student racial diversity in states that banned affirmative action, with a drastic rise in Hispanic enrollment shares. In contrast, the other three races remain unchanged. Further analysis by state legislative control indicates significant declines in Asian enrollment shares post-ban, solely in Democratic-led states.

This study contributes to finding underlying mechanisms for how student racial diversity has changed after banning affirmative action. Reductions in student racial diversity are derived from exclusive increases in Hispanic enrollment shares post-ban, which reflect Hispanic-student-oriented advantages in college admissions in the long term. Another mechanism is that state legislature partisanship creates variations in the effects of affirmative action bans. Differences in post-ban enrollment shares between Democratic and Republican-led states emphasize the importance of considering state legislature partisanship to measure policy effects, specifically for liberal policies like affirmative action.

The findings provide policy implications on the interactions among affirmative action bans, student racial diversity, and state political factors. U.S. higher education policies should consider the effects of student racial diversity on political and socioeconomic outcomes to address educational inequities post-ban. State political factors mediating the effects of such bans further broaden insights into statewide student racial diversity outcomes to analyze how student racial diversity outcomes differ across the states before and after such bans.

The paper proceeds as follows. Section II explains the historical background of affirmative action in U.S. higher education and literature reviews related to this study. Section III presents data and descriptive statistics collected for the analyses. Section IV develops the empirical strategy to calculate the racial diversity measure and the dynamic effects of affirmative action bans on the outcomes. Section V provides the main results of the analyses. Section VI discusses policy implications for various outcomes of student racial diversity post-ban. Section VII concludes with a summary of this study and relative future research topics.

II. Context

The context section provides an overview of the historical background of affirmative action in U.S. higher education and literature reviews on college-level racial diversity and policy effects by state legislature partisanship. The historical background explains the beginning and end of affirmative action policies in U.S. higher education to help understand contentious views supporting affirmative action in university admissions. The literature review focuses on three topics in the U.S. context: outcomes in previous research measuring the effects of affirmative action bans, the importance of racial diversity in higher education, and variations in policy effects by state legislature partisanship. From the body of the literature review, I address the research gap in the existing literature and how to fill the gap.

Historical Background

The historical background section summarizes the history of affirmative action in U.S. higher education with debates about its ban in 11 states. The history of affirmative action policies in U.S. higher education began with an effort to raise enrollment of under-represented minorities (URMs) across universities during the 1960s and 1970s (Arcidiacono et al., 2015; Bowen & Bok, 1998). President Lyndon B. Johnson signed Executive Order 11246 to offer URMs equal access to social resources by mandating government contractors to take affirmative action in employing URMs. Following his civil rights movement, higher education institutions (HEIs) across the U.S. have enacted affirmative action for their admission process, which provides additional consideration to a student's race or ethnicity for campus diversity and inclusion (Garrison-Wade & Lewis, 2004). Affirmative action in U.S. higher education has been formed by rulings of the U.S. Supreme Court, state-specific voters, or regulations without centralized legislation (Arcidiacono et al., 2015). The U.S. Supreme Court has never mandated affirmative action in college admissions, but the U.S. Supreme

Court has ruled a national precedent allowing HEIs to include race as one factor in making admission decisions *(Grutter v. Bollinger, 2003)*.

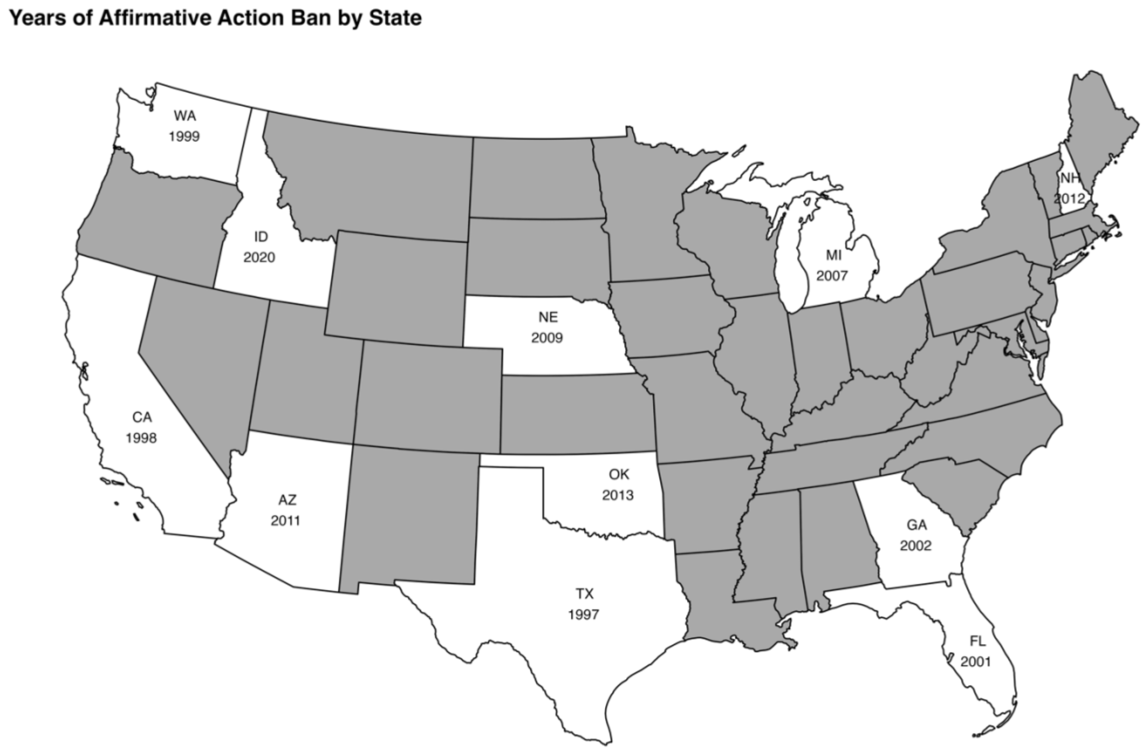
However, race-based affirmative action policies in U.S. college admissions have been controversial since *Regents of the University of California v. Bakke (1978)*, which is the first case of questioning the use of racial quotas in the admission process. Since then, discussions on continuing race-based affirmative action policies in U.S. higher education have been dichotomous across different states. Advocates for affirmative action in higher education maintain that affirmative action addresses historical disadvantages towards URMs to access high-quality education and increases student racial diversity on campus. In contrast, opponents of implementing affirmative action in college admissions support that banning race-based affirmative action could promote meritocracy and equity by emphasizing other factors of an applicant, such as academic achievement or socioeconomic background (Arcidiacono et al., 2015; Arcidiacono & Lovenheim, 2016; Garrison-Wade & Lewis, 2004; Hinrichs, 2012).

After controversial debates on affirmative action in U.S. higher education, several states have prohibited race-based affirmative action in public university admissions. Starting from Texas, state-level affirmative action bans have gone into effect through direct decisions made by voters, legislative action, or the U.S. Supreme Court ruling across 11 states from 1997 to 2020, as stated in Figure 1 (Antman & Duncan, 2015; Backes, 2012; Hinrichs, 2012, 2020).

In June 2023, these decade-long debates on whether to use race-based affirmative action in U.S. higher education ended with the final ruling of the U.S. Supreme Court on lawsuits against Harvard University and the University of North Carolina. The U.S. Supreme Court alleged that race-based affirmative action policies violate Title VI of the Civil Rights Act and the Equal Protection Clause of the 14th Amendment for Harvard University and the

University of North Carolina, respectively (*Students for Fair Admissions, Inc. v. President and Fellows of Harvard College, 2023*). The U.S. Supreme Court's recent decision on the nationwide race-based affirmative action ban in college admissions states that race can no longer be considered to widen access to postsecondary educational opportunities.

Figure 1
Affirmative Action Bans by State



Notes: The map indicates the years of banning affirmative action in U.S. public university admissions between 1990 and 2020, which are used to identify the timings of affirmative action bans in this study.

Affirmative Action Bans and U.S. Higher Education

This section introduces relative studies to this paper measuring the effects of banning affirmative action in U.S. higher education to address the research gap. Although the existing literature analyzes how affirmative action bans affect representations of URMs on campus, more needs to be known about the effects of such bans on overall student racial diversity. Prior research has primarily examined the effects of affirmative action bans in U.S. higher education on URMs' representations, mainly Black and Hispanic students. These studies analyze shifts in enrollment shares (e.g., Backes, 2012; Epple et al., 2008; Hinrichs, 2012; Long & Bateman, 2020; Long & Tienda, 2008), application behaviors (e.g., Antonovics & Backes, 2013; Arcidiacono, 2005; Bowen & Bok, 1998; Card & Krueger, 2005; Long, 2004; Rothstein & Yoon, 2008; Yagan, 2016), and racial segregation (e.g., Hinrichs, 2020; Howell, 2010) within public universities. For instance, while overall enrollment of Black and Hispanic students remained stable in public 4-year universities, their enrollments dropped within more selective universities after affirmative action bans (Backes, 2012; Epple et al., 2008; Hinrichs, 2012; Howell, 2010). Howell (2010) highlighted a 10% decline in URM enrollments at top-tier universities following race-neutral admission policies.

On the other hand, literature concentrating on states with substantial Black and Hispanic demographics reveals a significant disappearance of advantages for Black and Hispanic students post-ban (Arcidiacono, 2005; Long, 2004; Long & Bateman, 2020; Long & Tienda, 2008). Long and Bateman (2020) highlight a persistent decline in Black and Hispanic student enrollments at public universities in California and Texas. Hinrichs (2020) also addresses declines in the exposure of Black to White students (i.e., Black-White racial segregation) across public universities in California post-ban. His study suggests that the effects of affirmative action bans on racial segregation vary depending on the timing of a ban and the racial composition of state demographics (Hinrichs, 2020).

The broader effects of affirmative action bans on overall student racial diversity have not been thoroughly examined, nor have the differing policy effects across ban states. Past studies, particularly those focusing on California or Texas, have selected these states based on large populations of Black and Hispanic students rather than exploring state-specific factors that may affect policy effects in the first place (Arcidiacono et al., 2015; Hinrichs, 2020; Long, 2004; Long & Bateman, 2020; Long & Tienda, 2008).

The literature review shows little is known about changes in student racial diversity post-ban, as most previous studies focus on the effects of such bans on URMs' representations. The rest of the literature review explores the importance of student racial diversity in higher education and how state legislature partisanship affects policy effects, highlighting the need to analyze the effects of affirmative action bans on student racial diversity by state legislature partisanship.

Racial Diversity and Higher Education

Research about student racial diversity offers more extensive benefits to higher education. This section highlights the importance of college-level student racial diversity with its definitions and outcomes from educational and political perspectives. Student racial diversity, which refers to structural diversity on campus with numerical or proportional representations of racially diverse students, not only helps reduce racial segregation on campus but also enriches the learning environment, student satisfaction, and political identity (Akhtari et al., 2024; Astin, 1993; Billings et al., 2021; Gurin et al., 2009; Hurtado et al., 1999). Yet, the emphasis in existing literature on the effects of affirmative action bans has often been placed on URMs, overlooking the full spectrum of the effects of racial diversity on student learning. Increasing representations of URMs is crucial but is not equivalent to reducing racial segregation among various racial groups of students (Hinrichs, 2020).

The importance of racial diversity on college student outcomes underscores the need to focus on overall student racial diversity to attain a more holistic understanding of the effects of affirmative action bans. Student outcomes associated with racial diversity in higher education are mainly categorized as collaborative learning environments (e.g., Loes et al., 2018), academic development (e.g., Terenzini et al., 2001), and student democracy (e.g., Adida et al., 2023; Guarasci & Cornwell, 1997; Gurin et al., 2009).

HEIs with diverse student bodies provide collaborative learning environments with more educational benefits than racially homogeneous student bodies. At the college level, collaborative learning allows students to share interdependent work with others and identify misunderstandings about perspectives in the group, thereby improving students' communication skills and academic achievement (Loes et al., 2018). In terms of academic development, the racial diversity level of a student body provides a measurable impact on student learning gains. Students in racially diverse classrooms experience higher problem-solving and group communication skills than those in a medium-diversity classroom (Terenzini et al., 2001).

Furthermore, college racial diversity consistently boosts student democracy outcomes, such as citizenship engagement, perspective-taking, and inclusive political attitudes (Adida et al., 2023; Gurin et al., 2009). Previous studies reveal that school racial diversity can alter students' behavior toward URM groups and enhance long-run political behavior by fostering intergroup contact, which reduces sociopolitical prejudice (Billings et al., 2021; Carrell et al., 2019). In addition to the structural diversity on campus, diversity in university curriculums also shifts students' political attitudes. A study by Adida et al. (2023) highlights the importance of including ethnic diversity and multiculturalism-related materials in university courses for shaping more inclusive student attitudes towards diversity. Changes in student democracy outcomes through college racial diversity can be the foundation of democracy and political identity before stepping into a demographic-changing society with diverse nationalities.

Educational and student democracy outcomes with racially diverse student bodies in prior research support the significance of analyzing changes in student racial diversity post-ban. Analyses of student racial diversity post-ban will further contribute to research on different student outcomes that correspond to changes in student racial diversity.

State Legislature Partisanship and Policy Effects

This study examines changes in student racial diversity across U.S. public universities since 11 states banned affirmative action in college admissions between 1990 and 2020. In addition to racial compositions of pre-college state populations, this paper considers state legislative control to explore how state legislature partisanship shapes policy effects over time. Filling research gaps on the effects of affirmative action bans on student racial diversity sheds light on the broader effects of such bans across U.S. public universities. Furthermore, utilizing state legislature partisanship in analyses identifies state political factors driving different policy effects.

The state politics literature on the causal effects of state legislature partisanship on policy effects provides mixed results. Most studies using cross-sectional data find no significant impact of state legislature partisanship on ideological directions of state policies or policy liberalism (e.g., Erikson et al., 1993; Lax & Phillips, 2012; Plotnick & Winters, 1985). Some studies show a negative correlation between Democratic party control and high-level liberal policies, such as race-based affirmative action in college admissions, due to high incongruence values attributed to conservative public opinion in the early 2000s (Lax & Phillips, 2012).

However, another branch of literature on the causal effects of state legislature partisanship on state policies using panel data argues limitations of those findings with cross-sectional data. Caughey et al. (2017) highlight issues regarding identification strategy and generalization of other time periods with the results using cross-sectional data. These findings about the effects of state legislature partisanship on state policy can be biased by omitted variables confounding with state legislative control or selecting a single period when utilizing cross-sectional data. Previous studies using panel data to estimate the causal effects of state legislature partisanship on policies have employed more robust research designs with stronger identification strategies. Some of these studies find significant effects of state legislature partisanship on state policies, such as civil rights, tax burdens, and welfare (e.g., Chen, 2007; Reed, 2006; Kousser, 2002).

Caughey et al. (2017) expand the findings with dynamic panel analysis and show that partisan effects of state legislatures on policy have grown drastically in recent decades, which involves the greater ideological polarization between Democrats and Republicans. Their findings suggest that electing more Democrats than Republicans in state legislatures has led to more liberal roll call voting records and liberal policies, race-based affirmative action in U.S. college admissions, inter alia (Caughey et al., 2017; Caughey & Warshaw, 2018; Fowler & Hall, 2017; Lax & Phillips, 2012; Lee et al., 2004; Shor & McCarty, 2011). At the state level, policy areas with more polarization among local governments and public opinion, including race and redistribution policies, are affected by larger partisan effects (Warshaw, 2019). Thus, the effects of state legislature partisanship should be considered to measure the policy effects of affirmative action bans across the U.S. universities in-depth, as state legislative control can affect policy decisions about implementing affirmative action bans.

The historical background of affirmative action in U.S. higher education and the literature review provides comprehensive views of affirmative action bans in 11 states between 1990 and 2020. Furthermore, the research gap in the previous literature supports the contributions of this study that measures the effects of affirmative action bans on student racial diversity during the last 30 years and finds how state legislature partisanship varies the policy effects across the U.S.

III. Data

The data section explains a collection of data from 1990 to 2020 to measure changes in student racial diversity before and after banning affirmative action in U.S. public university admissions. This section introduces four different types of data in the dataset and their descriptive statistics.

Integrated Postsecondary Education Data System

The main data for this research is collected from the Integrated Postsecondary Education Data System (IPEDS), a university-year-level U.S. panel dataset from 1990 to 2020. IPEDS provides annual information on institutional characteristics and enrollment data, including each university's location and enrollment by race and gender, which is used to measure the racial composition of a student body. Observations in this study are limited to first-time enrolling full-time undergraduates at public 4-year universities in the IPEDS dataset.[1] Universities in the sample are located across the U.S., except for Alaska and U.S. Territories (e.g., America Samoa, District of Columbia, Guam, the Northern Mariana Islands, Puerto Rico, and the U.S. Virgin Islands), as institutions in those states do not report sufficient numbers of race variables required for a racial diversity measurement.

Race and ethnicity are used interchangeably in this study. The term race includes four races or ethnicities defined in the IPEDS dataset: Asian, Black, Hispanic, and White. Other races in the data are categorized as Unknown/Others (e.g., race/ethnicity are not known, two or more races, or American Indian/Alaska Native). Table A1 in Appendix A explains definitions of race terms from each dataset used in the study, including the four main races utilized for the analyses: Asian, Black, Hispanic, and White.

[1] Backes (2012) supports that the restriction of not including 2-year or private institutions in the IPEDS data does not offset the effects of statewide affirmative action bans on enrollment shares.

American Community Survey and U.S. Census

The university-year-level IPEDS data on the racial compositions of undergraduate enrollment share is supplemented with additional datasets. State-year-level racial compositions of pre-college demographics are derived from the American Community Survey (ACS) from 2000 to 2020 and the 1990 U.S. Census. The ACS 2000-2020 and 1990 U.S. Census datasets include the four main race variables (i.e., Asian, Black, Hispanic, and White) ranging from ages 15 to 19. I code responses indicating Hispanic ethnicity but not White as Hispanic, and White for responses identifying as White and non-Hispanic in the ACS and the U.S. Census datasets to match racial terms among the IPEDS, ACS, and U.S. Census datasets (Table A1).

National Conference of State Legislatures

The annual records of the U.S. state legislative partisan compositions from 1990 to 2020 are derived from the National Conference of State Legislatures (NCSL). NCSL's state legislature partisanship data is used to code whether a state has Democratic or Republican legislative control from 1990 to 2020. State legislative control is determined by the number of seats taken by Democratic or Republican senators and house representatives for the 1990s and early 2000s, which does not contain variables regarding the legislative control party.[2]

Descriptive Statistics

Descriptive statistics provide an overview of the dataset used in this study, mainly different timings of statewide affirmative action bans in public university admissions and changes in student racial compositions from 1990 to 2020. A state is categorized as a ban state if the state has applied an affirmative action ban that prohibits the consideration of race in admission procedures at public universities. Otherwise, a state is coded as a non-ban state.

[2] State legislative control includes split cases if the same number of seats are taken between Democratic and Republican senators or house representatives. Nebraska has unicameral state legislatures; therefore, its legislative control is coded as non-partisan (National Conference of State Legislatures, 2024).

Table 1 summarizes the timing of affirmative action bans by state using the year when an affirmative action ban was first implemented for public university admissions (Antman & Duncan, 2015; Backes, 2012; Hinrichs, 2012, 2020).[3]

Table 1
Timing of Affirmative Action Bans by State

Ban State	Years in Effect
Texas	1997
California	1998
Washington	1999
Florida	2001
Georgia	2002
Michigan	2007
Nebraska	2009
Arizona	2011
New Hampshire	2012
Oklahoma	2013
Idaho	2020

Table 2 presents summary statistics of racial compositions of undergraduate enrollment shares from 1990 to 2020. Column 1 of Table 2 shows the mean of the racial compositions in each university across all states in the dataset. White students are the most representative of these universities, followed by Black, Hispanic, and Asian students. Columns 2 and 3 of Table 2 indicate that universities in ban states have larger portions of Asian and Hispanic students than universities in non-ban states, whereas more Black and White students enroll in universities in non-ban states. Regardless of statewide affirmative action bans, Asian students are the least represented in all situations, while White students take the most significant portion among all races in every case. Figure 2 illustrates

[3] Previous studies treat Georgia differently. Backes (2012) categorizes Georgia as a ban state since the courts struck down race-based first-year admission policies of the University of Georgia in 2002. On the other hand, Hinrichs (2012, 2020) drops observations from Georgia with Alabama, Louisiana, and Mississippi as the author sees that these states experienced uncertain legal situations regarding affirmative action in college admission policies. The results are robust to dropping Georgia, Alabama, Louisiana, and Mississippi from the observations, and they are presented in the last section of robustness checks in Appendix B.

differences in the trends of undergraduate racial composition between ban and non-ban states from 1990 to 2020. Figure A1 in Appendix A includes the Unknown/Others race category in the undergraduate racial composition figures between ban and non-ban states, following Figure 2.

Table 2
Summary Statistics of Racial Composition

	All States (1)	Ban States (2)	Non-ban States (3)
Asian	0.046	0.064	0.037
	(0.087)	(0.105)	(0.075)
Black	0.165	0.148	0.173
	(0.220)	(0.194)	(0.231)
Hispanic	0.113	0.198	0.070
	(0.160)	(0.209)	(0.106)
White	0.563	0.450	0.619
	(0.294)	(0.275)	(0.287)
Unknown/Others	0.096	0.117	0.086
	(0.165)	(0.175)	(0.159)
Racial Diversity Measure	0.473	0.565	0.428
	(0.237)	(0.221)	(0.231)
Number of universities	1,777	704	1,073
Observations	28,204	9,361	18,843

Notes: Undergraduate enrollment shares are restricted to first-year undergraduates at public 4-year universities from 1990 to 2020. Results are means and standard deviations in parentheses at the university-year-level. Ban states refer to Table 1. Non-ban states do not include Alaska and U.S. territories (e.g., America Samoa, District of Columbia, Guam, the Northern Mariana Islands, Puerto Rico, and the U.S. Virgin Islands). Unknown/Others include respondents selecting race/ethnicity unknown, other races, two or more races, American Native, or Alaska Native for their race and ethnicity. Racial diversity measure is calculated by 1-s_i^2, which s_i denotes the proportion of students of the same race at a university i who are Asian, Black, Hispanic, or White.

Figure 2
Racial Composition of Undergraduate Enrollment

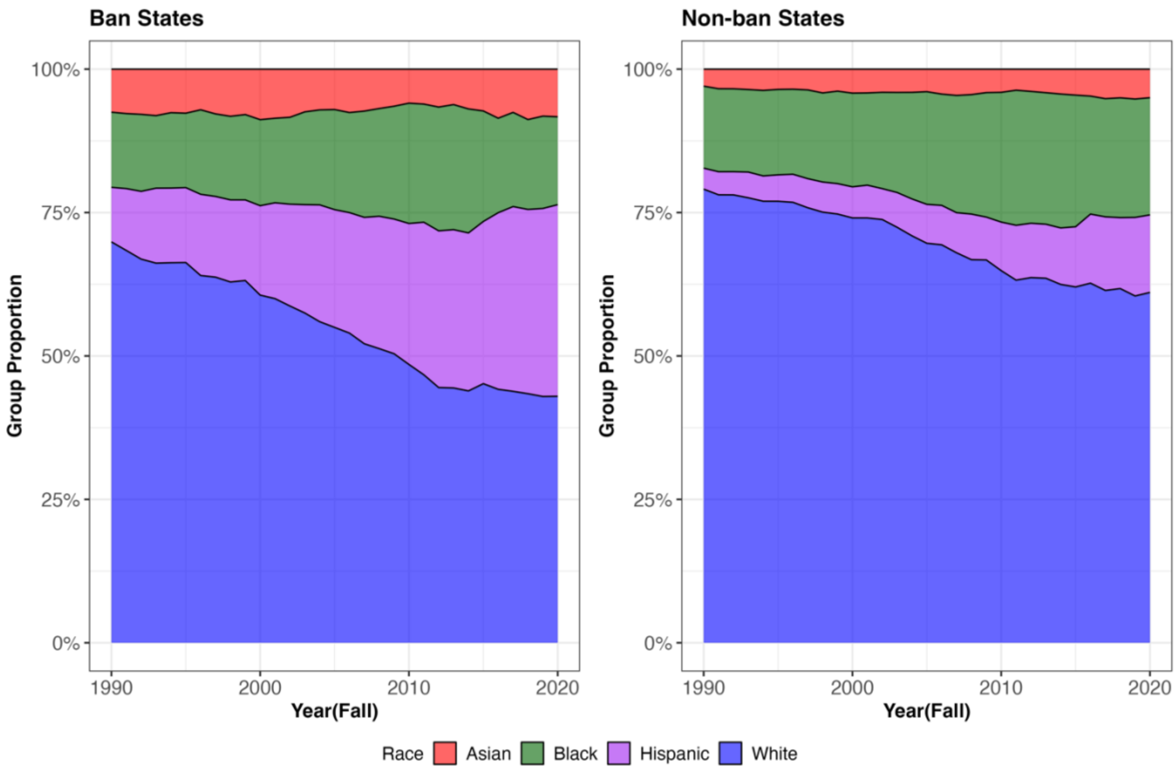


Table 3 provides a baseline for understanding differences in the racial compositions of undergraduates between public universities in ban states (i.e., later implemented affirmative action bans) and those that did not. Column 4 of Table 3 shows that baseline racial compositions between universities in ban and non-ban states were different even before affirmative action bans. However, differences in initial characteristics should be interpreted with caution since the racial composition of the data is based on the attributes of state-specific demographics, not a particular sample. The following empirical strategy section will explain how to control these baseline differences in racial compositions among states.

Table 3
Baseline Characteristics of Racial Composition

	All States (1)	Ban States (2)	Non-ban States (3)	Differences (4)
Asian	0.044	0.072	0.033	0.039
	(0.085)	(0.113)	(0.068)	[0.003]
Black	0.137	0.126	0.142	-0.016
	(0.219)	(0.194)	(0.228)	[0.007]
Hispanic	0.063	0.116	0.042	0.074
	(0.112)	(0.155)	(0.081)	[0.005]
White	0.718	0.631	0.752	-0.121
	(0.264)	(0.261)	(0.258)	[0.009]
Unknown/Others	0.029	0.038	0.026	0.011
	(0.081)	(0.068)	(0.086)	[0.002]
Racial Diversity Measure	0.321	0.424	0.281	0.143
	(0.204)	(0.209)	(0.187)	[0.007]
Number of universities	693	212	481	
Observations	4,357	1,225	3,132	

Notes: Baseline undergraduate enrollment shares are restricted to first-year undergraduates at public 4-year universities from 1990 to 1996 before Texas's first ban in 1997. Results are means and standard deviations in parentheses at the university-year-level. Column 4 reports the raw difference in means between columns 2 and 3 with standard errors in brackets. Ban states refer to Table 1. Non-ban states do not include Alaska and U.S. territories (e.g., America Samoa, District of Columbia, Guam, the Northern Mariana Islands, Puerto Rico, and the U.S. Virgin Islands). Unknown/Others include respondents selecting race/ethnicity unknown, other races, two or more races, American Native, or Alaska Native for their race and ethnicity.

Table 4 and Figure 3 show the partisan composition of state legislatures from 1990 to 2020. Ban states have larger portions of Republican state legislatures than non-ban states, while Democratic state legislatures take more seats in non-ban states. State legislatures include senators and house representatives, and Nebraska's state legislatures are stated as nonpartisan because of its single-house system.

Table 4

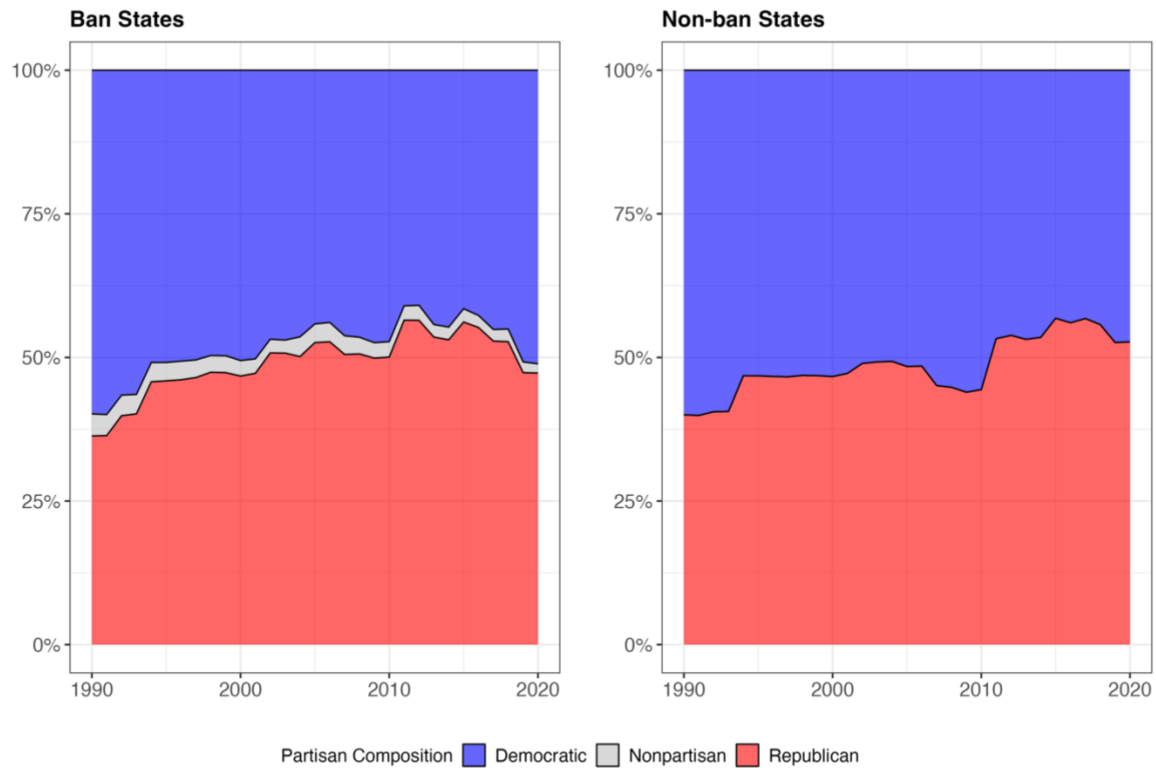
Summary Statistics of State Legislature Partisan Composition

	All States (1)	Ban States (2)	Non-ban States (3)
Democratic	0.494	0.468	0.507
	(0.149)	(0.152)	(0.146)
Republican	0.493	0.501	0.488
	(0.150)	(0.157)	(0.147)
Nonpartisan	0.009	0.026	0.000
	(0.093)	(0.160)	(0.000)
Number of states	49	11	38
Observations	343	77	266

Notes: Results are means and standard deviations in parentheses at the state-year-level from 1990 to 2020. Democratic is defined as the total number of Democratic senators and house representatives divided by the total seats for each state and year. Republican is defined as the total number of Republican senators and house representatives divided by the total seats for each state and year. Nonpartisan includes Nebraska's legislatures, which are elected on a nonpartisan basis. Ban states refer to Table 1. Non-ban states do not include Alaska and U.S. territories (e.g., America Samoa, District of Columbia, Guam, the Northern Mariana Islands, Puerto Rico, and the U.S. Virgin Islands).

Figure 3

State Legislature Partisan Composition



IV. Empirical Strategy

Racial Diversity Measure

This study adopts the ethno-linguistic-fractionalization (ELF) measure to calculate the racial diversity of undergraduates across universities in different years (Easterly & Levine, 1997). The ELF measure is derived from the Herfindahl concentration formula (i.e., 1-Herfindahl concentration) and has larger values corresponding to higher diversity levels (Boydstun et al., 2014; Posner, 2004).

The racial diversity measure assesses racial diversity among four main races in the data at the university-year level. The formula of the racial diversity measure is:

$$Racial\ Diversity\ Measure = 1 - \sum_{i=1}^{N} s_i^2 \tag{1}$$

In Equation 1, s_i denotes the proportion of first-time, full-time undergraduates of the same race at a university i who are Asian, Black, Hispanic, or White. A measure of 0 signifies homogeneity, whereas 1 represents maximum diversity (i.e., greater dispersion of racial groups). As a university has more diverse racial groups of students, its racial diversity measure becomes closer to 1.

Staggered Difference-in-Differences Model

This paper uses difference-in-differences (DiD) research designs to measure the difference between the change in student racial diversity and racial enrollment shares before and after affirmative action bans in ban versus non-ban states. Estimated coefficients from DiD identify the average effects of such bans on the ban states from 1990 to 2020. DiD eliminates bias from simple comparisons of the treatment effects pre- and post-ban under the common trends assumption (Goodman-Bacon, 2021). The dataset from 1990 to 1996 provides pre-ban trends of student racial diversity before banning affirmative action, and from 1997 to 2020, the dataset presents post-ban changes in student racial diversity since Texas's first ban in 1997.

In addition to Texas, affirmative action bans were implemented in different years across 11 states, as shown in Figure 1 and Table 1. Staggered introductions of affirmative action bans create varying treatment timelines and effects, leading to the considerations of heterogeneous average treatment effects (ATTs) across universities in ban states (Antonovics & Backes, 2013; Backes, 2012; Bleemer, 2021; Hinrichs, 2012, 2020). The first approach uses the staggered DiD with two-way fixed effects (TWFE) to address heterogeneous treatment effects across states. The DiD model in this study is written as:

$$Y_{ist} = \beta Ban_{st} + X_{st} + \theta_{is} + \tau_t + \varepsilon_{ist} \tag{2}$$

In Equation 2, Y_{ist} includes two types of outcomes: the racial diversity measure and enrollment shares of a particular race (e.g., Asian, Black, Hispanic, or White) at university i, located in state s, at year t. β is the parameter of interest, which measures the effects of such bans on the racial diversity measure and racial enrollment shares. Ban_{st} indicates the implementation of a ban. It equals 1 for treated state s from year t on and 0 otherwise.

X_{st} refers to control variables, which help control the baseline differences among states that may affect the outcome variables. X_{st} includes the racial composition of pre-college populations and state legislative control dummies by state and year. The racial composition of pre-college populations covers individuals aged 15 to 19 who are Asian, Black, Hispanic, or White in state s at year t. The state legislative control dummies indicate whether a state legislative control party is Democratic or Republican in year t. Nebraska, a unicameral state, is coded as non-party. The state legislative control dummies address different policy effects of affirmative action bans that might arise from differences in partisan control of state legislatures (Caughey et al., 2017; Wright & Schaffner, 2002). The specifications also include university-state and year-fixed effects, which are θ_{is} and τ_t, respectively. ε_{ist} is the error term, capturing unobserved heterogeneity.

The second approach is to utilize the staggered DiD model in event study formats to estimate dynamic treatment effects in different years before and after banning affirmative action. The second model using the staggered DiD in event study designs is formulated as:

$$Y_{ist} = \sum_{t \neq -1} \beta_t \, Ban_{st} + X_{st} + \theta_{is} + \tau_t + \varepsilon_{ist} \quad (3)$$

In Equation 3, Y_{ist} indicates the racial diversity measure and enrollment shares of the four races at university i, located in state s, at year t. β_t measures the dynamic effects of affirmative action bans on the outcomes for t years of the exposure to affirmative action bans, excluding one year before a ban. The rest of the variables are consistent with Equation 2. X_{st} controls the time-varying effects of the racial composition of pre-college populations and state legislative controls to tackle baseline differences across states (Caughey et al., 2017).

The parallel trend assumption of this study is that the outcomes in ban and non-ban states would have no difference in the absence of a ban over time. Also, previous research on the effects of affirmative action bans in U.S. higher education provides evidence of the exogeneity of affirmative action bans (Backes, 2012; Hinrichs, 2012, 2020).

V. Results

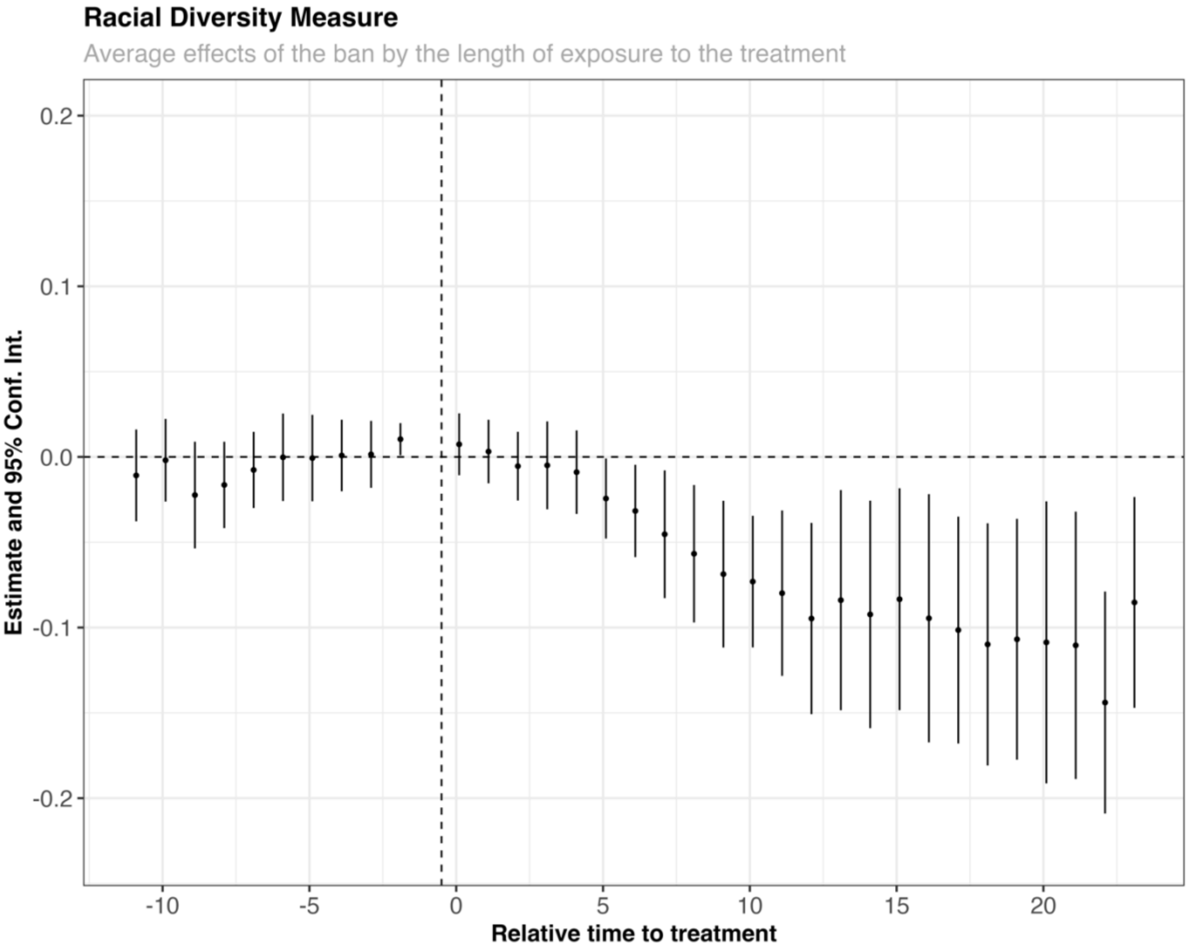
The results section explains the effects of affirmative action bans on student racial diversity and racial enrollment shares using the ELF measure and staggered DiD models. The last part of this section examines differences in the effects of such bans on the outcomes by state legislative control. The analysis shows how changes in state legislature partisanship create distinct policy effects across states.

Effect of Affirmative Action Bans on Racial Diversity

The analyses present that affirmative action bans in public university admissions have significantly reduced student racial diversity. Figure 4 shows the results of event studies based on Equation 3, with one year before the treatment as the reference year (i.e., $t = -1$), employing the DiD model. Figure 4 reveals that the racial diversity of full-time undergraduates at public 4-year universities has decreased after banning affirmative action in college admissions. The downtrend in the post-ban periods supports that affirmative action bans have negatively affected overall student racial diversity across universities in ban states.

The estimates in the pre-ban periods do not include significant differences from zero, satisfying the parallel trends assumption. Thus, universities sharing similar state characteristics would follow similar trends in student racial diversity in the absence of a ban, considering the control variables.

Figure 4
Time-Varying Effects of Affirmative Action Bans on Racial Diversity



Notes: Each dot represents the point estimate of the treatment effect in each year before and after the treatment (i.e., leads and lags) based on Equation 3; vertical lines on point estimates are the corresponding 95% confidence intervals. The reference year is -1, which is marked as a dashed vertical line. The specification includes the same variables as shown in Equation 3.

Table 5 contains the effects of affirmative action bans on the racial diversity measure across universities from 1990 to 2020, based on Equation 2. All models incorporate both sets of university-state and year-fixed effects to mitigate potential biases arising from varying trends across states and universities over time.

The first model in column 1 of Table 5 does not include any control variables, suggesting a 2.7 percentage points decrease in the racial diversity measure after affirmative action bans. In contrast, accounting for state racial compositions of the pre-college populations and the state legislative control variables refines the estimates. The third model in column 3 of Table 5 shows an overall decrease of 2.9 percentage points in the racial diversity measure following affirmative action bans, with all control variables included. Given the non-ban state baseline mean racial diversity measure of 0.281 in Table 3, affirmative action bans have reduced student racial diversity of ban states by approximately 10.32%.

The treatment effects with all control variables indicate that both demographic compositions and state legislature partisanship are crucial in assessing the effects of affirmative action bans on student racial diversity.

Table 5
Effects of Affirmative Action Bans on Racial Diversity

	Racial Diversity Measure		
	(1)	(2)	(3)
Ban_{st}	-0.027	-0.025*	-0.029*
	(0.018)	(0.012)	(0.012)
University-state fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Control variables			
X_{st}	No	Yes	Yes
$Party_{st}$	No	No	Yes
Adjusted R^2	0.346	0.347	0.348
Observations	28,204	28,204	28,204

Notes: Standard errors clustered at the state level are in parentheses. X_{st} indicates the racial composition of pre-college populations aged 15 to 19, who are Asian, Black, Hispanic, or White in state *s* in year *t*. $Party_{st}$ includes state legislative control dummy variables, which are Dem_{st} and REP_{st}. Dem_{st} equals 1 when a state legislative control party is Democratic in state *s* in year *t* while REP_{st} equals 1 when a state legislative control party is Republican in state *s* in year *t*.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Effect of Affirmative Action Bans on Racial Enrollment

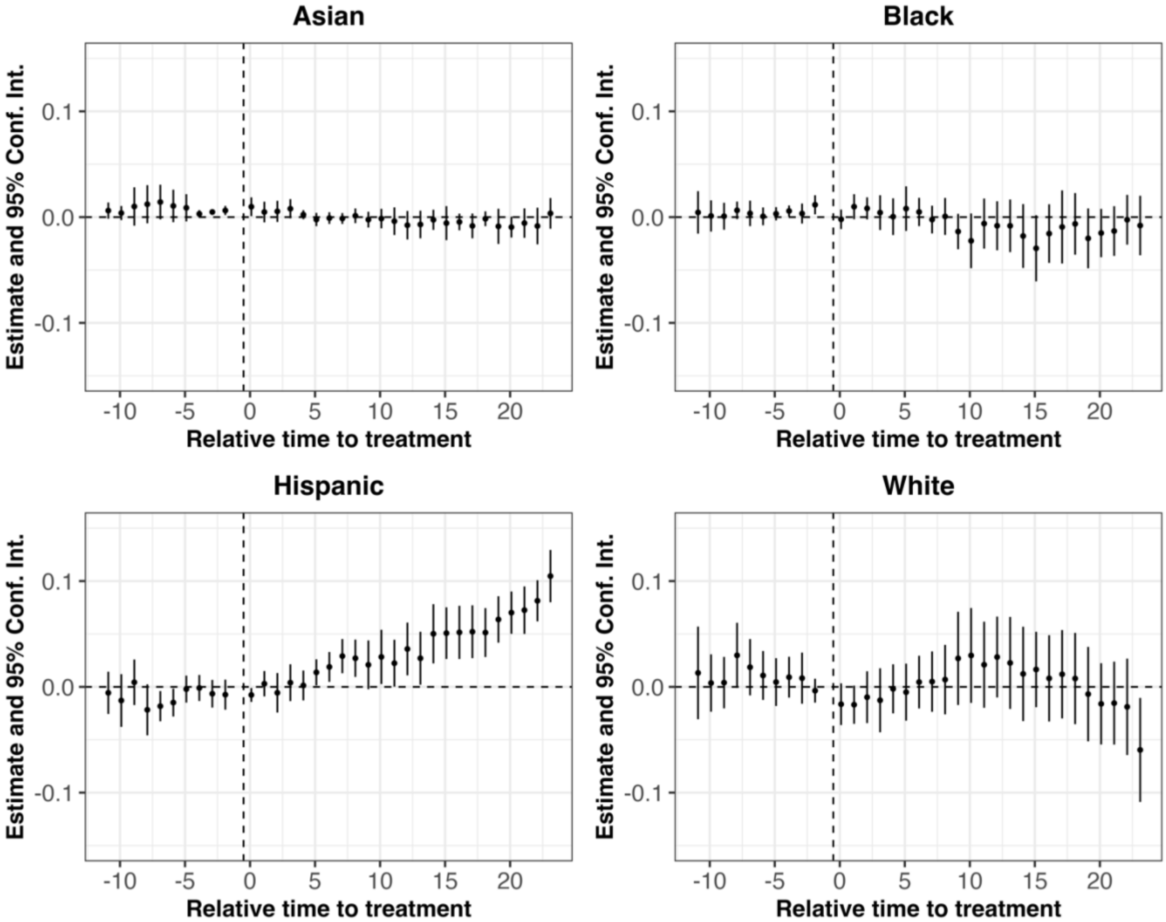
The analyses of shifts in racial enrollment shares help identify how changes in racial enrollment shares affect student racial diversity post-ban. The results show that affirmative action bans have increased Hispanic enrollment shares solely. The exclusive rise in Hispanic enrollment shares accounts for the decline in the racial diversity measure post-ban.

Figure 5 indicates the dynamic effects of affirmative action bans on enrollment shares of the four races (i.e., Asian, Black, Hispanic, and White) based on Equation 3, with the same specifications as Figure 4. Implementations of affirmative action bans have not changed the overall trends of enrollment shares of Asian, Black, and White students. The treatment effects on enrollment shares of these three races lack statistical significance, with most confidence intervals being close to the zero bound in the post-ban periods.

Unlike the other three races, Hispanic enrollment shares have increased overall five years after affirmative action bans. The upward trend in the Hispanic figure has continued during the post-ban periods and appears statistically significant over time, indicating substantial effects of affirmative action bans on Hispanic enrollment shares. The dynamic effects of affirmative action bans on Hispanic enrollment shares suggest that more Hispanic students attain opportunities to study at public universities after banning affirmative action in college admissions.

Figure 5

Time-Varying Effects of Affirmative Action Bans on Racial Enrollment



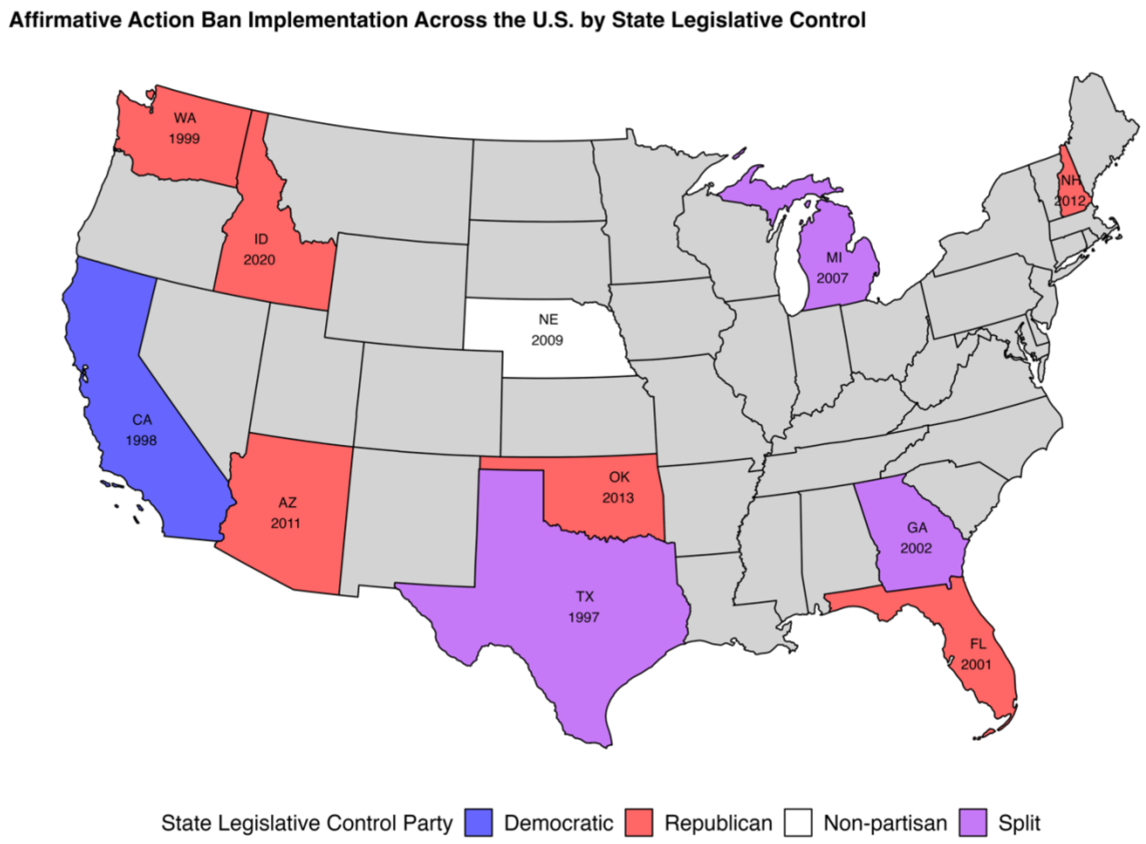
Difference in Policy Effect by State Legislative Control

This section examines whether the effects of affirmative action bans on the outcomes differ between states controlled by Democratic and Republican legislatures over time. Analyzing the distinct effects of affirmative action bans by state legislative control is crucial to understanding how state legislature partisanship varies the policy effects.

Figure 6 provides an overview of different state legislative control parties when public universities in each state banned affirmative action in their admission processes. I divide the dataset by state legislative control dummy variables (i.e., Democratic and Republican) and test each subset data with all fixed effects and control variables as in column 3 of Table 5 for Figure 7 and Figure 8.

Figure 6

Affirmative Action Bans by State Legislative Control



Notes: State legislative control is split when different parties hold the state chambers, while state legislative control can be either Democratic or Republican when the same party holds both chambers (National Conference of State Legislatures, 2024). Legislatures in Nebraska are elected on a non-partisan basis.

The effects of affirmative action bans on the racial diversity measure do not significantly differ between states controlled by Democratic and Republican legislatures. Figure 7 shows that the racial diversity of undergraduates has continuously decreased since affirmative action bans, regardless of state legislative control. Differences in the estimates are not significant between the two cases with all control variables, as presented in columns 2 and 4 of Table 6.

In contrast, Figure 8 contains distinct effects of affirmative action bans on racial enrollment shares between states controlled by Democratic and Republican legislatures. Changes in enrollment shares of Asian undergraduates are significantly different between states led by Democratic and Republican legislatures. At the same time, the other three races indicate consistent trends post-ban regardless of state legislative control. Asian enrollment shares have reduced after affirmative action bans in Democratic-led states, which is not observed in Republican-led states.

The gap in Asian enrollment shares between Democratic and Republican-led states suggests that affirmative action bans displace Asian students from public universities in states with Democratic legislative control, and their effects are greater on Asian students in Democratic-led states. The difference in Asian enrollment shares supports the importance of considering state legislative control to measure the statewide effects of such bans.

Figure 7
Time-Varying Effects on Racial Diversity by State Legislative Control

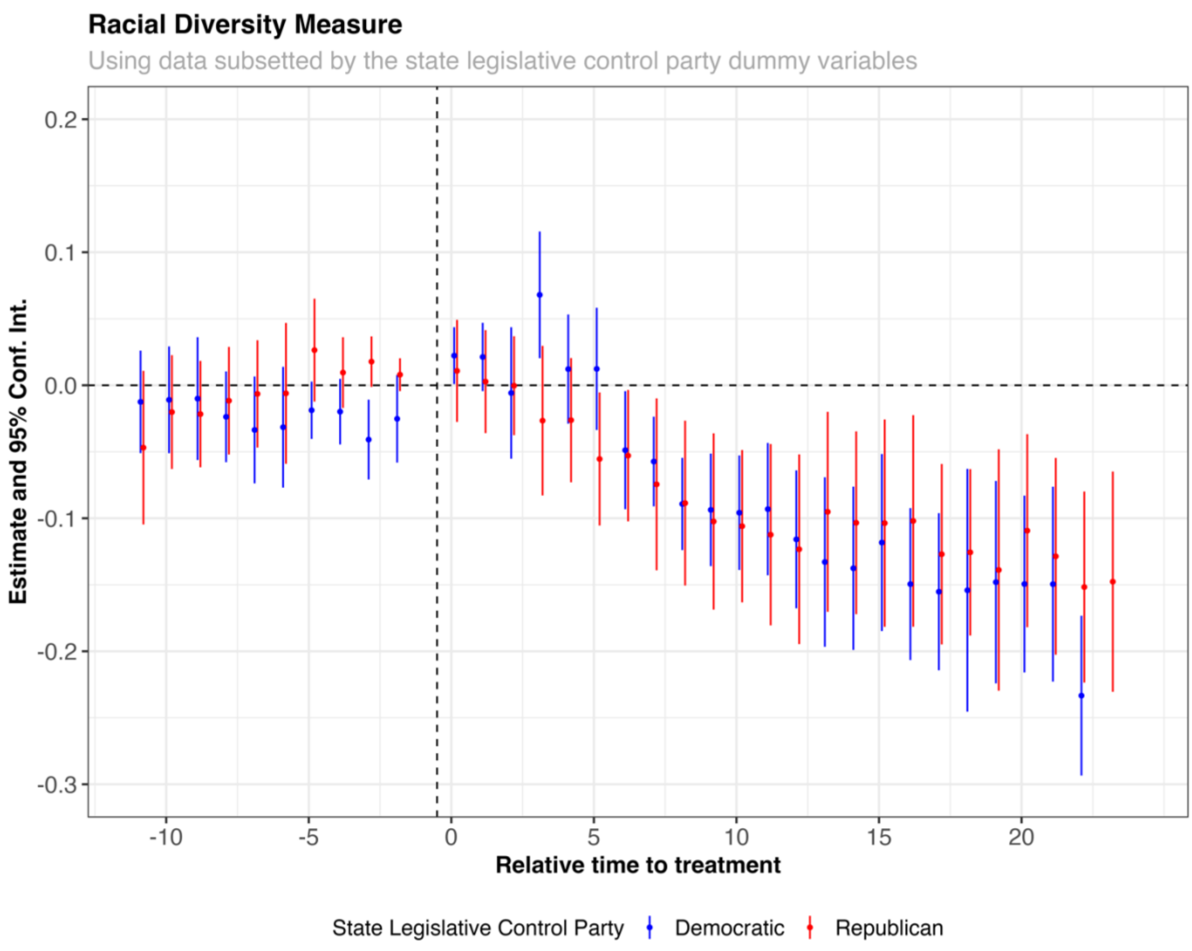


Table 6

Effects of Affirmative Action Bans on Racial Diversity by State Legislative Control

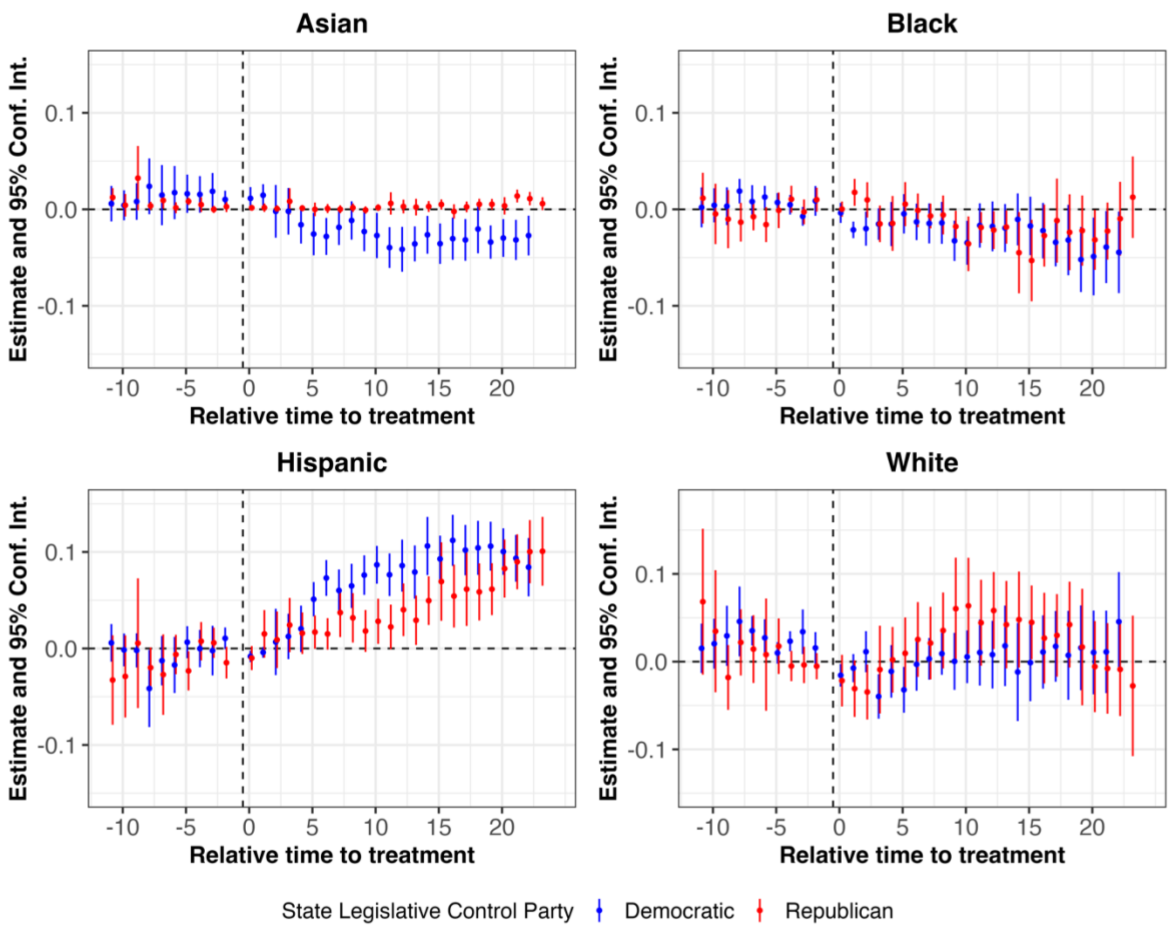
	Racial Diversity Measure			
	Democratic		Republican	
	(1)	(2)	(3)	(4)
Ban_{st}	-0.072***	-0.036	-0.042	-0.037
	(0.016)	(0.023)	(0.029)	(0.023)
University-state fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
X_{st}	No	Yes	No	Yes
Adjusted R^2	0.446	0.448	0.251	0.253
Observations	10,048	10,048	12,222	12,222

Notes: Standard errors clustered at the state level are in parentheses. X_{st} indicates the racial composition of pre-college populations aged 15 to 19, who are Asian, Black, Hispanic, or White in state s in year t. Democratic refers to a subsample of the main data consisting of states with Democratic legislative control in year t, while Republican indicates a Republican subsample. Nebraska is not included in both subsamples as it has unicameral state legislatures.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 8

Time-Varying Effects on Racial Enrollment by State Legislative Control



VI. Discussion

This paper identifies how affirmative action bans affect student racial diversity and reveals differences in its effects by state legislative control. The findings of this paper suggest two critical underlying mechanisms. Firstly, decreases in the racial diversity measure after banning affirmative action are derived from drastic increases in Hispanic enrollment shares post-ban. Different from Asian, Black, and White students, more Hispanic students have been advantaged in college admissions in the long term since affirmative action bans across U.S. public universities. As a result of the exclusive rise in Hispanic enrollment shares, the overall racial diversity of undergraduates has decreased post-ban.

The exclusive increase in Hispanic enrollment shares post-ban indicates that banning affirmative action in college admissions provides advantages for Hispanic students in public university admissions. A study by Hinrichs (2020) shows that Hispanic exposure to Whites has increased at public 4-year universities since affirmative action bans. His research supports the idea that affirmative action bans increase access to public universities for Hispanic students. Another external factor affecting the rise in Hispanic enrollment shares between 1990 and 2020 could be percent plans. Texas passed the Top Ten Percent Plan (TTP) in 1997, and Florida issued the One Florida Plan in 1999 to guarantee autonomic state public university admissions without SAT or ACT scores to high school seniors in the top decile of their class. Earlier research demonstrates the positive effects of TTP on significant increases in URMs' enrollment at top public universities (Daugherty et al., 2014). Hispanic students may benefit from TTP and affirmative action bans for their public university admissions.

The second mechanism found in this study is that state legislature partisanship creates variations in the effects of affirmative action bans across states. State legislature partisanship is crucial to consider in measuring the effects of these bans on racial composition shifts, particularly in Democratic-led states. Differences in Asian enrollment shares post-ban between Democratic and Republican-led states support the idea that state legislative control creates variations in state policy effects (Lax & Phillips, 2012).

Although this study examines the effects of affirmative action bans on student racial diversity considering state legislature partisanship, there are several other considerations beyond the scope of the paper. Some URM students may attend less selective colleges instead of top-tier colleges due to the reduced slots in selective colleges in favor of URM students (Arcidiacono & Lovenheim, 2016; Backes, 2012; Hinrichs, 2020). If affirmative action bans significantly place URM students in less selective universities, the ranking of the universities would need to be considered to identify more precise effects of such bans on the racial diversity measure. For instance, controls including university rankings or types will allow researchers to discover in what types of colleges the effects of affirmative action bans on student racial diversity are stronger. Moreover, the effects of affirmative action bans could differ between public and private universities. Further studies could analyze the effects of such bans on student racial diversity using observations from private U.S. universities.

Other important factors that should be considered include mass policy preferences on affirmative action bans by state. For implementations of economic or social policies highly affected by mass policy preferences, such as affirmative action bans, both distinct state public opinion and party control create variation in the policy effects (Caughey & Warshaw, 2018; Lax & Phillips, 2012). Applications of mass policy preferences will provide more detailed mechanisms of the effects of affirmative action bans on student racial diversity, such as relationships between mass policy preferences and state legislature partisanship, creating different policy effects in each state. Additional institutional characteristics and mass policy preference variables will help estimate more precise effects of affirmative action bans on student racial diversity and racial enrollment shares from multiple perspectives.

VII. Conclusion

This study analyzes the effects of affirmative action bans on student racial diversity and racial enrollment shares at U.S. public universities from 1990 to 2020. The first set of analyses reveals that banning affirmative action in public university admissions has reduced undergraduate racial diversity in ban states by 10.32% on average.

The following analyses show the effects of affirmative action bans on racial enrollment shares. Affirmative action bans lead to a sharp increase in Hispanic enrollment shares, while Asian, Black, and White students do not experience significant changes post-ban. The declines in student racial diversity are associated with the exclusive increase in Hispanic enrollment shares after banning affirmative action in public university admissions.

The third set of analyses presents the distinct effects of affirmative action bans on the outcomes based on state legislative control. Democratic-led states show significant decreases in Asian enrollment shares post-ban, while all racial enrollment shares in Republican-led states indicate the same trends as the main results. Regardless of the state legislative control and choice of staggered DiD estimators, the racial diversity measure has decreased, and Hispanic enrollment shares have increased following affirmative action bans.

This paper provides an avenue for future research on the interactions among affirmative action bans, student racial diversity, and state political factors. Ultimately, further research can estimate the effects of racial diversity on political, economic, or educational outcomes before and after banning affirmative action in college admissions. Areas of research that are relevant to student racial diversity outcomes include college effects, peer effects in academic performance, political identity, and political party registration depending on student racial diversity post-ban (Adida et al., 2023; Arcidiacono & Lovenheim, 2016; Backes, 2012; Billings et al., 2021; Hinrichs, 2020). As affirmative action bans will be implemented nationwide, this paper suggests more attention to student racial diversity outcomes post-ban.

Focusing on student racial diversity outcomes will extend our understanding of the relationships between racial diversity and socioeconomic capital or political attitudes toward various racial groups. Furthermore, research on the statewide effects of affirmative action bans on racial diversity outcomes broadens insights into political domains mediating state policy effects and racial diversity outcomes. This study thus contributes to understanding the mechanisms for how affirmative action bans affect student racial diversity and how state legislature partisanship creates variations in the policy effects across the U.S.

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Appendix A. Supplemental Information

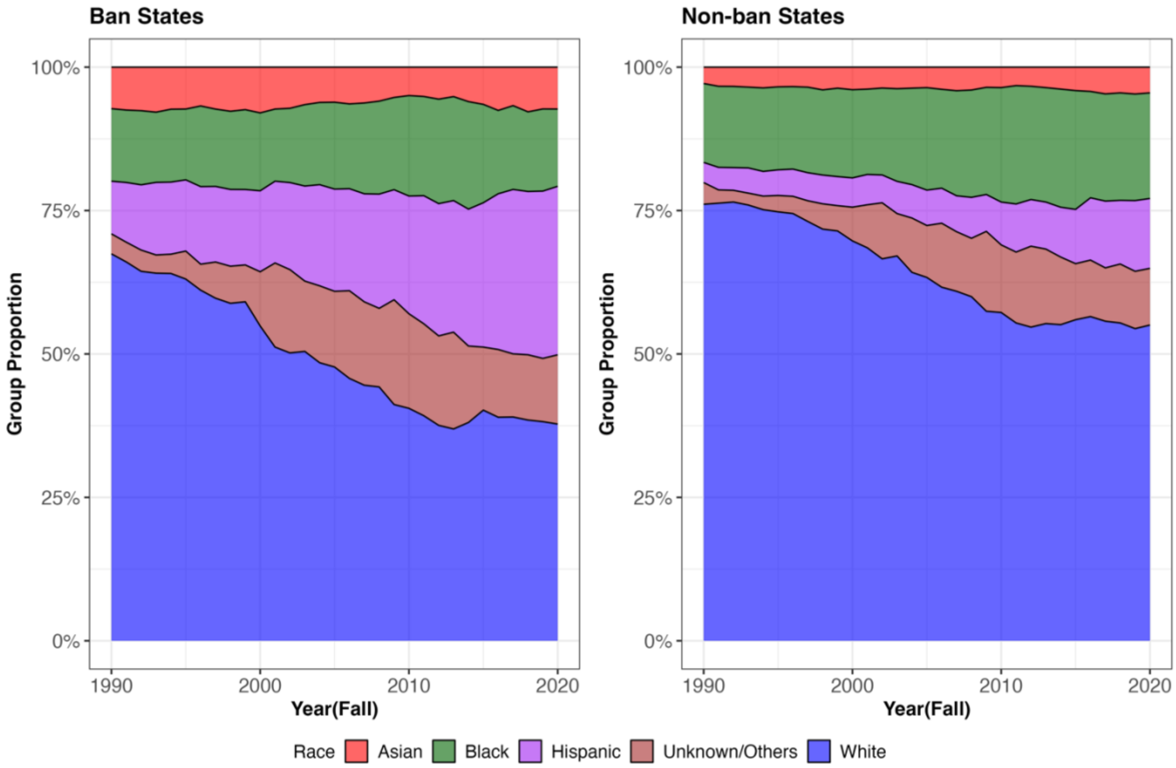
Table A1
Race/Ethnicity Category Description

Category	Data	Description
Asian; Native Hawaiian or Pacific Islander	IPEDS	A person having origins in any of the original peoples of the Far East, Southeast Asia, the Indian Subcontinent, or Pacific Islands, including countries such as China, Japan, Korea, the Philippines, American Samoa, India, and Vietnam
	ACS, U.S. Census	The population of people who are Asian alone or in combination; The population of people who are Native Hawaiian or Pacific Islander alone or in combination
Black; African American; Non-Hispanic	IPEDS	A person having origins in any of the Black racial groups of Africa, except those Hispanic origins
	ACS, U.S. Census	The population of people who are Black alone or in combination
Hispanic; Latino	IPEDS	A person of Mexican, Puerto Rican, Cuban, Central or South American, or other Spanish cultural or ethnic backgrounds, regardless of race
	ACS, U.S. Census	Persons of Hispanic/Spanish/Latino origin and classifies them according to their country of origin when possible
White; Non-Hispanic	IPEDS	A person having origins in any of the original peoples of Europe, North Africa, or the Middle East, except those of Hispanic origin
	ACS, U.S. Census	The population of people who are White alone or in combination
American Indian or Alaskan Native	IPEDS	A person having origins in any of the original peoples of North America and who maintains cultural identification through tribal affiliation or community recognition
	ACS, U.S. Census	A person's race or races include American Indian or Alaska Native
Others; Two or More Races	IPEDS	Persons who selected more than one race
	ACS, U.S. Census	The population of people who are some other races, alone or in combination
Race/Ethnicity Unknown	IPEDS	This category is used only if the student did not select either a racial or ethnic designation
	ACS, U.S. Census	N/A

Sources: ACS and U.S. Census: Ruggles, S., Flood, S., Sobek, M., Brockman, D., Cooper, G., Richards, S., & Schouweiler, M. (2023). *IPUMS USA: Version 13.0* [dataset]. IPUMS. https://doi.org/10.18128/D010.V13.; IPEDS: U.S. Department of Education, National Center for Education Statistics. (2023). *Integrated Postsecondary Education Data System (IPEDS): 1990-2020* [dataset]. Institutional Characteristics/Fall Enrollment. https://nces.ed.gov/ipeds/use-the-data

Figure A1

Racial Composition of Undergraduate Enrollment, Five Races



Notes: Figure A1 includes the Unknown/Others race category in addition to the four races (i.e., Asian, Black, Hispanic, and White) used in Figure 2. Unknown/Others refers to observations categorized under these three categories in Table A1: American Indian or Alaskan Native; Others/Two or More Races; and Race/Ethnicity Unknown.

Appendix B. Robustness Checks

Imputation-based DiD Estimator

Robustness checks are crucial in this study to analyze the validity of the results, considering the recent advances in DiD models. Recent advances in econometric literature on DiD highlight potential biases in the conventional DiD model with TWFE when treatments span multiple periods (Baker et al., 2022; Borusyak et al., 2024; Callaway & Sant'Anna, 2021; De Chaisemartin & D'Haultfœuille, 2020; Gardner, 2022; Goodman-Bacon, 2021; Roth et al., 2023; Sun & Abraham, 2021). In staggered policy implementations like affirmative action bans, traditional approaches potentially produce contaminated ATTs due to heterogeneous treatment effects derived from varying treatment timelines that create not-yet-treated, already-treated, or later-treated universities across states (Goodman-Bacon, 2021). Additionally, employing ordinary least squares (OLS) estimators in the traditional dynamic event study settings can lead to negative weighting problems when already-treated universities act as control units, further complicating the analysis (De Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021; Sun & Abraham, 2021).

For robustness checks, I adopt an imputation-based DiD estimator of Borusyak et al. (2024) to counter heterogeneous treatment effects in the staggered nature of affirmative action bans and compare the estimates to the DiD model used in the main analyses. The imputation-based DiD estimator provides a robust estimator of the effects of affirmative action bans on the racial diversity measure in its imputation procedure. The imputation procedure begins with estimating the university and time-fixed effects using only untreated universities. These estimated fixed effects are then used to impute the untreated potential outcomes for the treated observations, allowing the calculation of an estimated treatment effect for each treated unit. Finally, a weighted sum of these treatment effect estimates is used with the weights of the specific estimation target (Borusyak et al., 2024).

The imputation-based DiD estimator separates the process of estimation from testing estimates, allowing the resolution of inference problems after pre-testing untreated observations. The imputation-based DiD estimator utilizes all pre-treatment periods as a reference category, thereby providing more conservative cohort-average treatment effect estimates. The imputation process also considers any shifts in state legislative control over the years that may affect the outcomes (Borusyak et al., 2024). Therefore, using all pre-treatment periods for the estimates enables the imputation-based DiD estimator to include a stronger identification assumption of no anticipation than other DiD estimators robust in staggered setups (e.g., Callaway & Sant'Anna, 2021; De Chaisemartin & D'Haultfœuille, 2020; Sun & Abraham, 2021), which rely on a single pre-event period to calculate ATTs.

Figure B1 and Figure B2 compare the dynamic effects of affirmative action bans on the racial diversity measure and racial enrollment shares using two different DiD estimators: the imputation-based DiD estimator and the DiD model. Both models are tested in the event study format based on Equation 3 with one year before the treatment as the reference year (i.e., $t = -1$). They include the same control variables (i.e., state-year-level aged 15-19 racial composition variables and state legislative control variables), university-state and year-fixed effects. Standard errors of all models are clustered at the state level.

Similar trends in both figures support the validity of the DiD model used in the main analyses. Figure B1 and Figure B2 present the decrease in the racial diversity measure and the increase in Hispanic enrollment shares since affirmative action bans, regardless of the choice of the DiD estimator. However, the imputation-based DiD estimator provides more precise confidence intervals in the post-ban periods compared to the DiD model. Differences in confidence intervals indicate the efficacy of the imputation-based DiD estimator in capturing heterogeneous dynamics of staggered treatments with time-varying controls.

The imputation-based DiD estimator specifically captures significant reductions in Asian and Black enrollment shares post-ban in Figure B2. Figure B2 shows declines in enrollment shares of Asian and Black undergraduates since affirmative action bans with the DiD imputation estimator, although the effect is not large in magnitude. In contrast, the treatment effects on Asian and Black enrollment shares are statistically insignificant when measured by the DiD model, including wider confidence intervals being close to the zero bound in the post-ban periods.

Figure B1
DiD Imputation Estimates on Racial Diversity

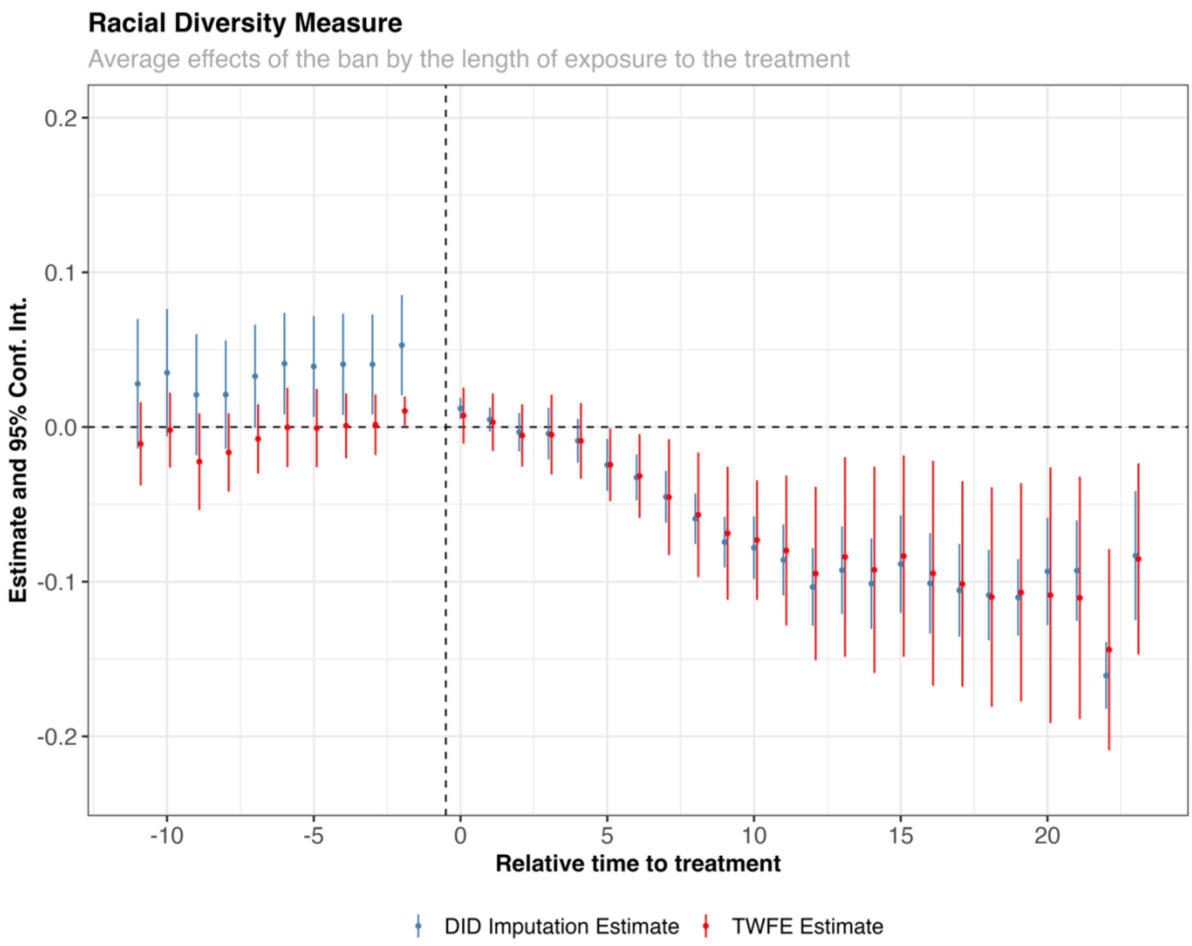
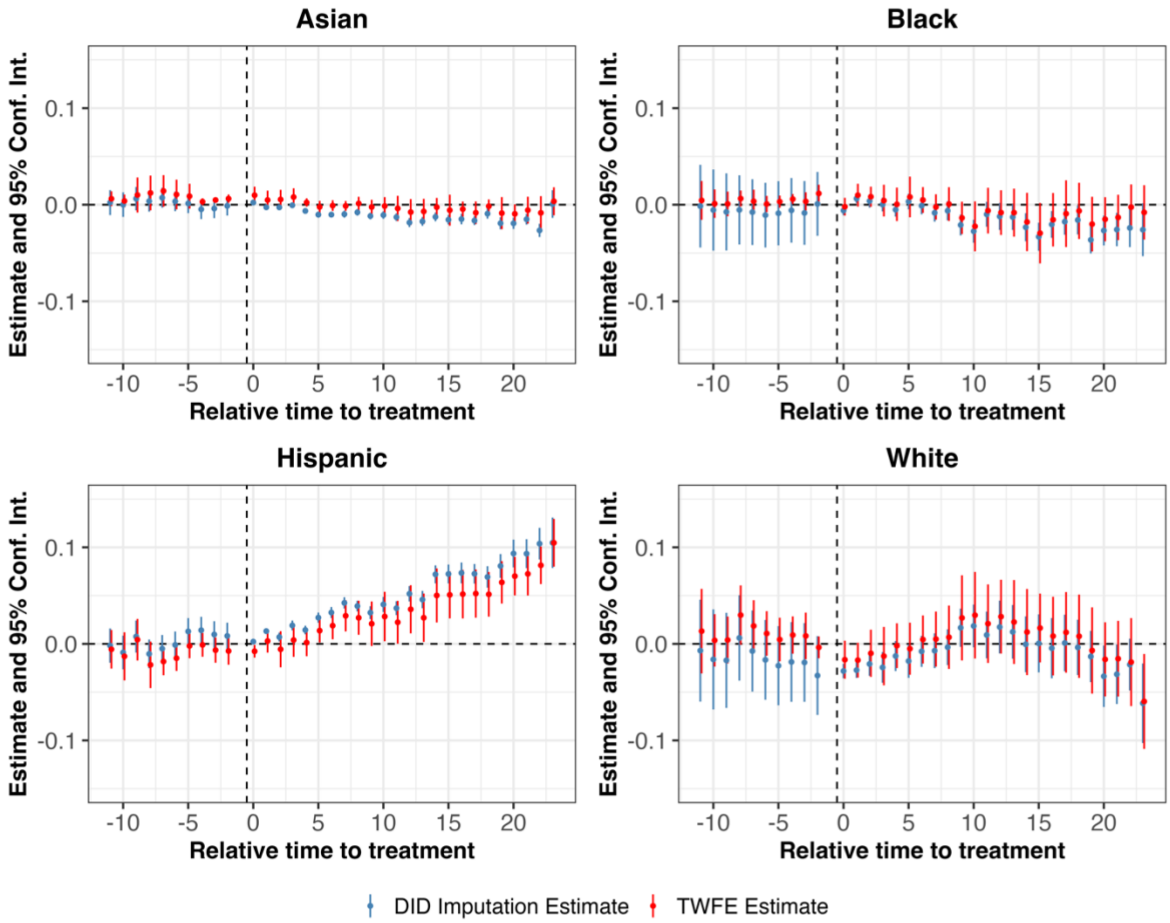


Figure B2

DiD Imputation Estimates on Racial Enrollment



The second set of robustness checks provides the effects of affirmative action bans on the outcomes by state legislative control using the imputation-based DiD estimator. The effects of such bans on student racial diversity measured by the imputation-based DiD in Figure B3 are similar to the analysis using the DiD model in Figure 7. However, notable differences between those two models are observed from Black enrollment shares in Figure B4. Figure B4 presents larger declines in Black enrollment shares in Democratic and Republican-led states after affirmative action bans, which are shown as insignificant changes with the DiD model used in Figure 8.

Differences in the Black figures between Figure 8 and Figure B4 arise from limitations of regression-based estimation to identify heterogeneous treatment effects in the staggered rollout with relatively smaller observations. With a small sample, the imputation-based DiD estimator provides a stronger identification assumption since regression-based estimation leverages comparisons between newly-treated and earlier-treated groups (Borusyak et al., 2024).

Meanwhile, the DiD and imputation-based DiD models provide similar trends for Asian, Hispanic, and White students in Figure 8. After such bans, Asian enrollment shares have decreased in Democratic-led states, Hispanic enrollment shares have increased in both cases, and there is no significant impact on White students.

Figure B3

DiD Imputation Estimates on Racial Diversity by State Legislative Control

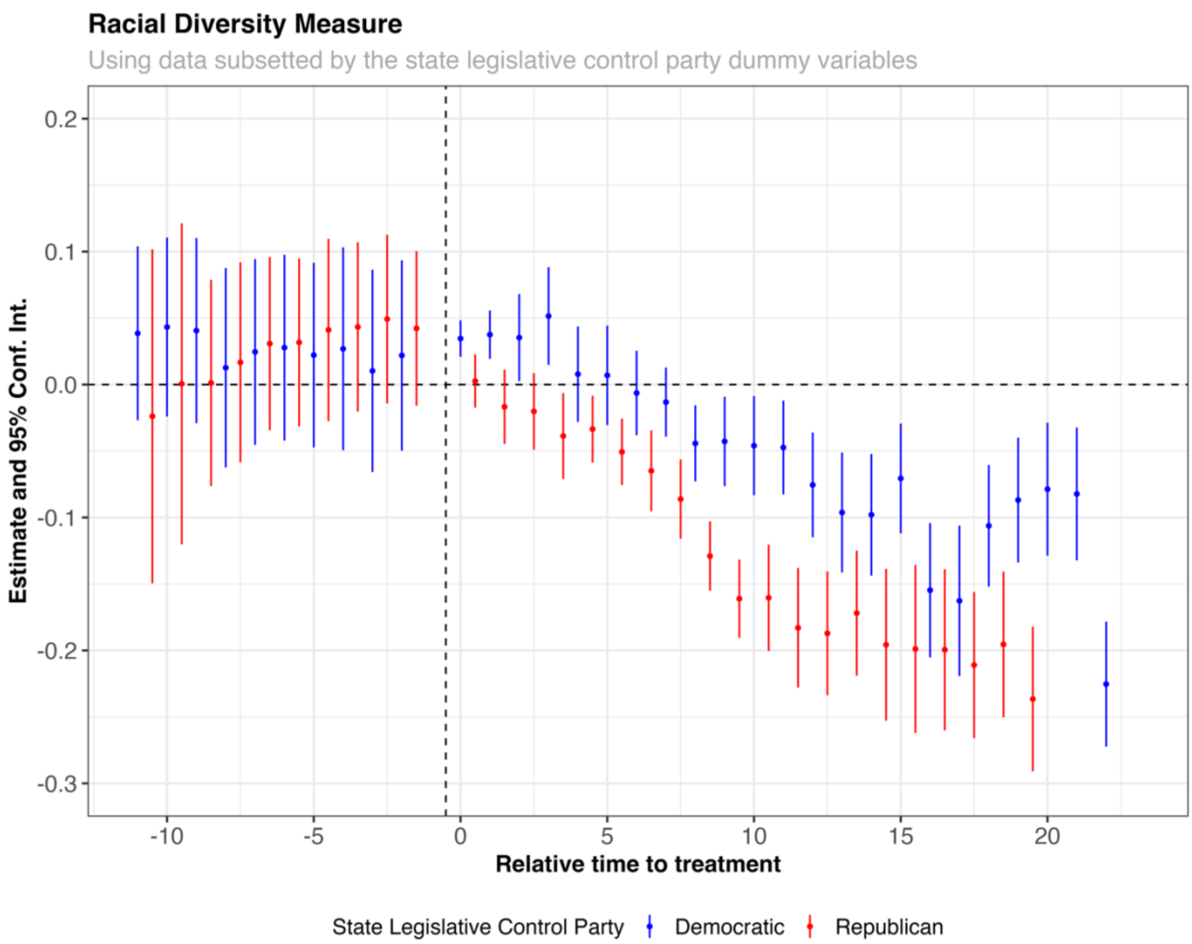
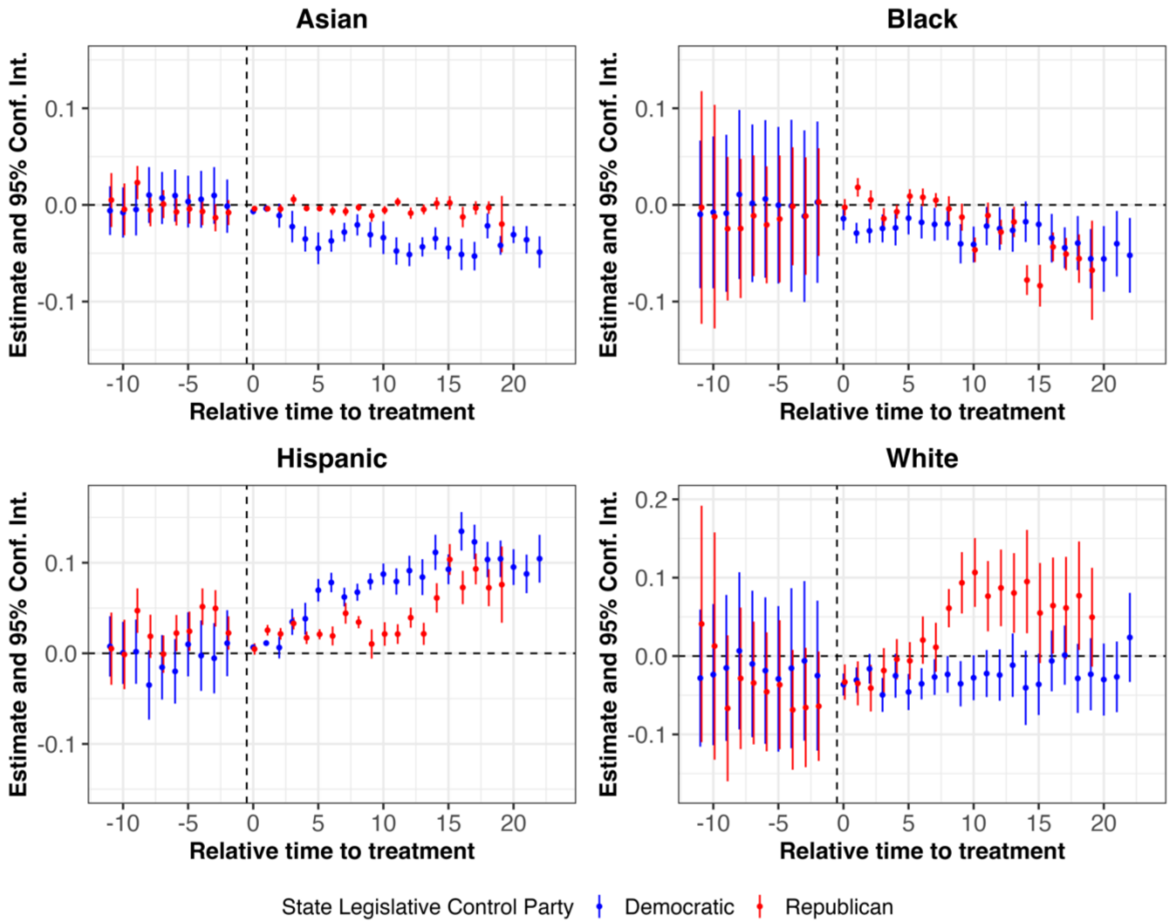


Figure B4

DiD Imputation Estimates on Racial Enrollment by State Legislative Control



Alternative Staggered DiD Estimators

The third set of robustness checks provides estimates of alternative DiD estimators to check the validity of the DiD model used in this study. Table B1 includes the estimated effects of affirmative action bans on the racial diversity measure with alternative staggered DiD estimators, which are all robust to the research setting where treatment effects vary by timing and group.

The imputation-based DiD estimator, DiD_{imp} in column 1 of Table B1, is compared to several alternatives. The alternatives begin with widely used staggered DiD estimators, DiD_{cs} and DiD_{sa} in columns 2 and 3 of Table B1. DiD_{cs} employs the group-time ATT approach by Callaway and Sant'Anna (2021), and DiD_{sa} utilizes interacted regression approaches by Sun and Abraham (2021). PSM in column 4 combines a propensity score matching (PSM) methodology with the imputation-based DiD estimator for a refined analysis, and $CBPS$ in column 5 of Table B1 incorporates a covariate balancing propensity score matching (CBPS) with the imputation-based DiD.

Compared to DiD_{imp} and other alternatives, DiD_{cs} estimates are relatively lower. The difference in estimates arises from different approaches to estimating ATTs and selecting control groups. DiD_{cs} calculates the overall ATTs by averaging state-year specific ATTs, which are estimates for each state that implemented a ban in a particular year. These estimates are then compared by outcomes from one year before the ban to after, using control groups from states without a ban. Thus, variations captured across states and years by DiD_{cs} potentially result in lower ATTs compared to other estimators. Other than DiD_{cs}, the estimates from staggered DiD estimators of DiD_{imp} and DiD_{sa} in columns 1 and 3 of Table B1 are similar to the baseline results but show larger declines in magnitude. Compared to the 2.9 percentage points decline using the DiD model in Table 5, the results with DiD_{imp} and DiD_{sa} show reductions of 6.7 percentage points and 5.7 percentage points in the racial diversity measure, respectively.

PSM and CBPS, used in columns 4 and 5 of Table B1, limit the control group to a set of units that are more comparable or similar. I consider universities that banned affirmative action in the following year as a treated group and universities that have never been banned as the control group. Then, I use PSM and CBPS to match to one control university with a close estimated propensity or covariate balancing propensity of being treated based on university-year or state-year-level characteristics for each treated university. The characteristics include the racial composition of undergraduates and dummies for the controlling party of state legislatures. Matching datasets using PSM and CBPS are then incorporated with the imputation-based DiD estimator to measure the average effects of affirmative action bans on the racial diversity measure during the periods. Finally, the estimates measured through PSM and CBPS in columns 4 and 5 of Table B1 show significant decreases in the racial diversity measure post-ban. On average, affirmative action bans have reduced student racial diversity by 5.8 percentage points with PSM in column 4 and 8.2 percentage points with CBPS in column 5 of Table B1.

Table B1
Alternative Staggered DiD Estimates on Racial Diversity

	Racial Diversity Measure				
	DiD_{imp} (1)	DiD_{cs} (2)	DiD_{sa} (3)	PSM (4)	$CBPS$ (5)
Ban_{st}	-0.067***	-0.019	-0.057***	-0.058**	-0.082***
	(0.010)	(0.013)	(0.010)	(0.028)	(0.016)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	28,204	26,926	28,204	13,524	8,954

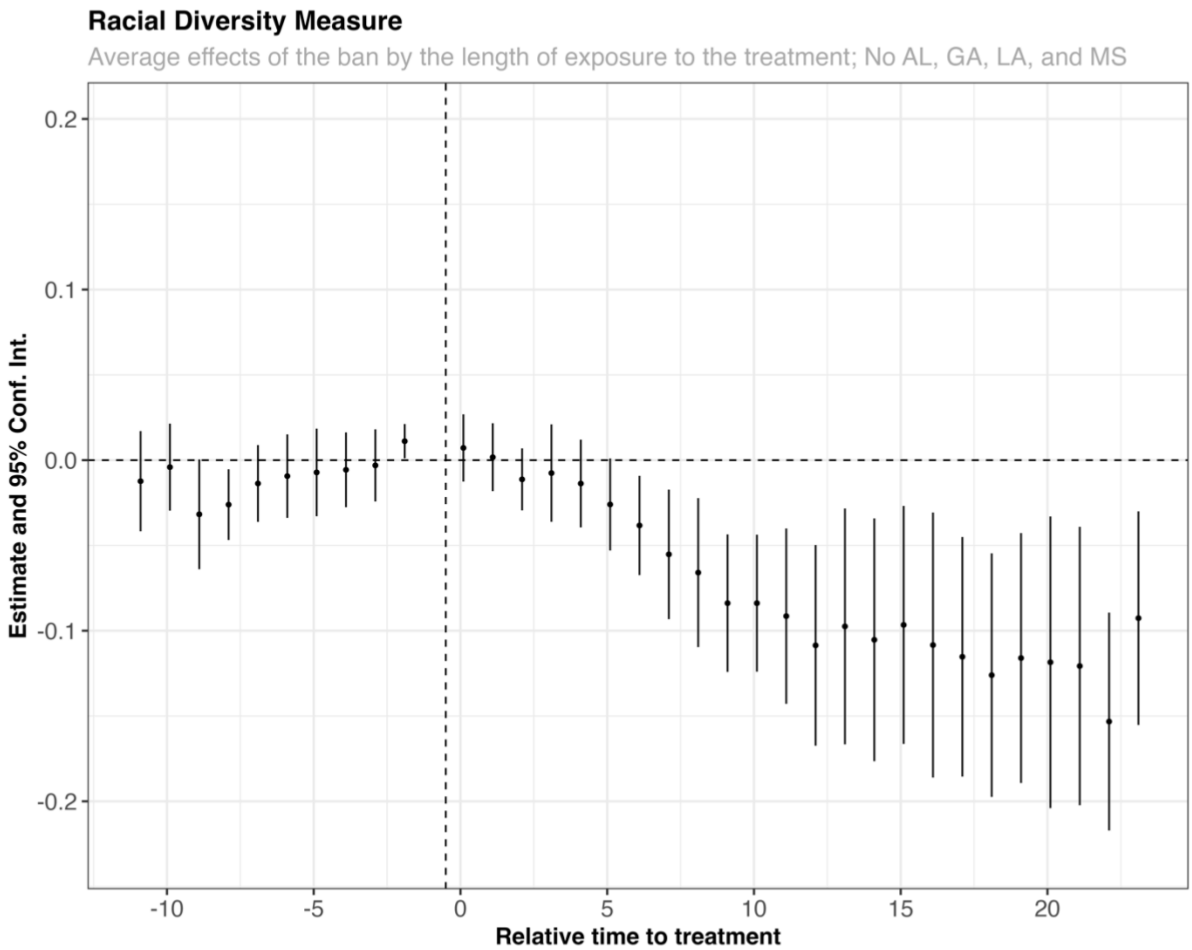
Notes: Standard errors clustered at the state level are in parentheses. Controls include all control variables and fixed effects applied in column 3 of Table 5. For *PSM* and *CPBS*, university-year-level enrollment variables, such as headcounts of full-time Asian, Black, Hispanic, White, and non-resident undergraduates, are additionally used to enhance the matching process. The R packages used for each analysis in Table B1 are: didimputation for column (1); did for column (2); fixest for column (3); matchit for column (4); CBPS for column (5).
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Results Without Four States

The last set of robustness checks reviews the effects of affirmative action bans on the main outcomes when four states, Alabama, Georgia, Louisiana, and Mississippi, are excluded from the observations. I apply the DiD model to a dataset dropping these four states to support the robustness of the main results following Backes (2012) and Hinrichs (2012, 2020). Since previous studies treat Alabama, Georgia, Louisiana, and Mississippi differently, I drop these four states from the observations as Hinrichs (2020), so they are neither categorized as ban states nor non-ban states.

Figure B5 shows the dynamic effects of affirmative action bans on the racial diversity measure using the dataset excluding the four states. Compared to the baseline event study results for the same periods presented in Figure 4, there are no significant differences between Figure B5 and Figure 4. The similarity between these two figures verifies the robustness of the main results, including Georgia as a ban state and Alabama, Louisiana, and Mississippi as non-ban states.

Figure B5
Time-Varying Effects on Racial Diversity Without Four States



Notes: Each dot represents the point estimate of the treatment effect in each year before and after the treatment (i.e., leads and lags) based on Equation 3; vertical lines on point estimates are the corresponding 95% confidence intervals. The reference year is -1, which is marked as a dashed vertical line. The specification includes the same variables as shown in Figure 4. Different from Figure 4, Figure B5 excludes observations from Alabama, Georgia, Louisiana, and Mississippi as Hinrichs (2020).

Table B2 presents the effects of affirmative action bans on the racial diversity measure in a static DiD format as shown in Table 5, but universities in Alabama, Georgia, Louisiana, and Mississippi are excluded from the observations. The DiD model without these four states also shows a significant decline in student racial diversity since affirmative action bans, with the same baseline fixed effects and controls.

Table B2

Effects of Affirmative Action Bans on Racial Diversity Without Four States

	Racial Diversity Measure		
	(1)	(2)	(3)
Ban_{st}	-0.034	-0.025	-0.029*
	(0.020)	(0.014)	(0.014)
University-state fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Control variables			
X_{st}	No	Yes	Yes
$Party_{st}$	No	No	Yes
Adjusted R^2	0.357	0.359	0.360
Observations	25,832	25,832	25,832

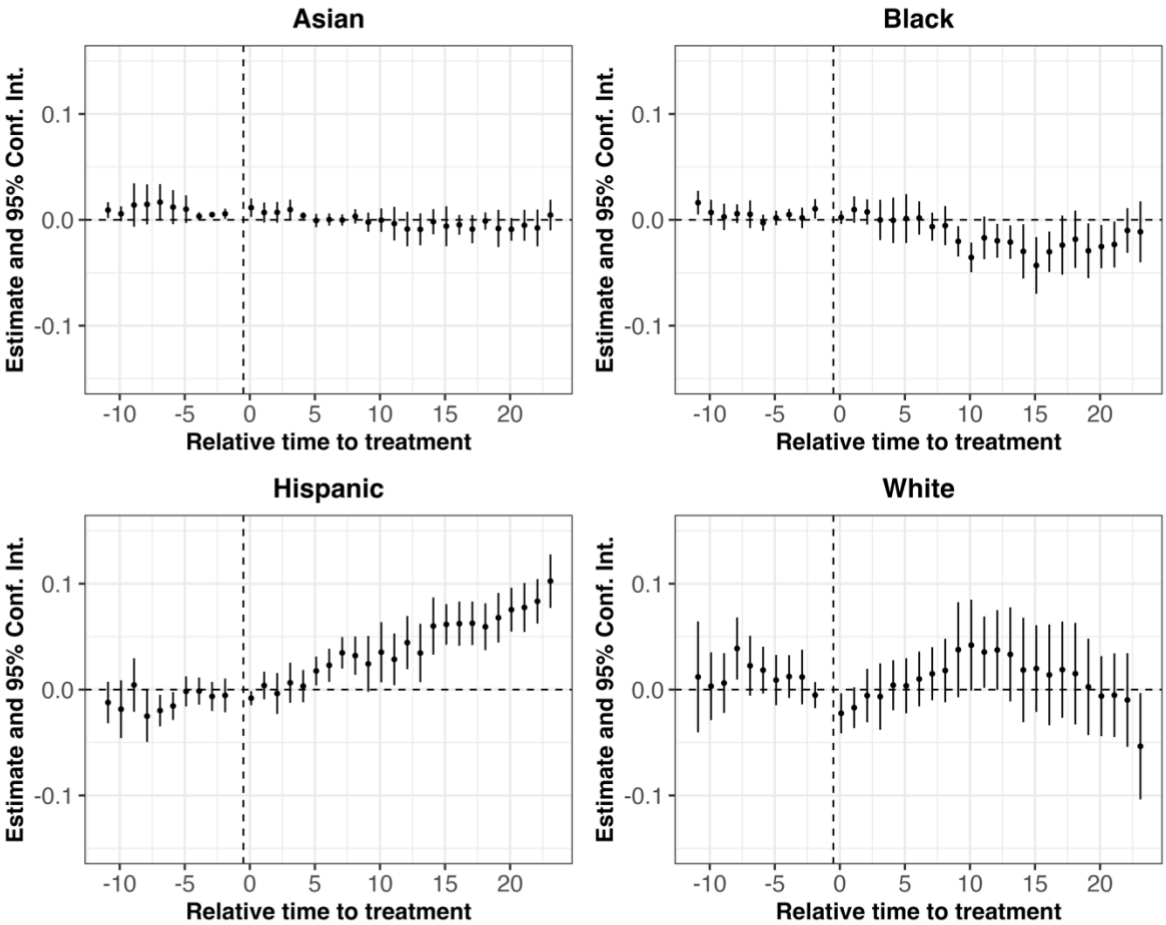
Notes: Standard errors clustered at the state level are in parentheses. X_{st} indicates the racial composition of pre-college populations aged 15 to 19, who are Asian, Black, Hispanic, or White in state *s* in year *t*. $Party_{st}$ includes state legislative control dummy variables, which are Dem_{st} and REP_{st}. Dem_{st} equals 1 when a state legislative control party is Democratic in state *s* in year *t* while REP_{st} equals 1 when a state legislative control party is Republican in state *s* in year *t*. Different from Table 5, Table B2 excludes observations from Alabama, Georgia, Louisiana, and Mississippi as Hinrichs (2020).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Lastly, the outcome of racial enrollment shares without the four states is presented in Figure B6. The only difference between Figure B6 and Figure 5 is the exclusion of the four states in the analysis; considering the same control variables, the trends for each race remain the same. There are no significant differences among the figures and tables compared to the baseline results. The last set of robustness checks proves that the baseline estimates are similar to the analyses without the four states. Therefore, the last set of robustness checks supports the validity of including Georgia as a ban state while categorizing Alabama, Louisiana, and Mississippi as non-ban states in the main analyses.

Figure B6

Time-Varying Effects on Racial Enrollment Without Four States



Notes: The specification includes the same variables as shown in Figure 5. Different from Figure 5, Figure B6 excludes observations from Alabama, Georgia, Louisiana, and Mississippi as Hinrichs (2020).