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Affirmative Action and Mismatch: Evidence from Statewide Affirmative Action Bans

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Abstract

This paper empirically evaluates the mismatch hypothesis by exploiting the quasi-experimental variation in the adoption of statewide affirmative action bans. Specifically, this paper examines the effect of such bans on minority graduation rates using a difference-in-difference, synthetic control, and triple-difference approach. My results suggest that statewide affirmative action bans are associated with an increase in minority graduation rates, consistent with the mismatch hypothesis, at highly selective institutions. Moreover, mismatch effects are not confined to science, technology, engineering, and math (STEM) majors. *JEL Codes*: I28, J15

Keywords

Mismatch, Government Policy, Educational Policy, Economics of Minorities, Affirmative Action

Cover Page Footnote

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1. Introduction

The use of racial preferences in admissions decisions at postsecondary institutions has ignited contentious political and socioeconomic debate. Proponents of "affirmative action" programs maintain that increased racial diversity at colleges and universities benefit White and Asian (nonminority) students and promotes the equitable treatment of historically disadvantaged minority groups. In his 1965 commencement address at Howard University, President Lyndon B. Johnson memorably captured affirmative action's *raison d'être*: "You do not take a person who, for years, has been hobbled by chains and liberate him, bring him up to the starting line of a race and then say, 'You are free to compete with all the others,' and still justly believe that you have been completely fair." In a landmark 1978 decision, the U.S. Supreme Court upheld the constitutionality of affirmative action programs in *Regents of the University of California v. Bakke*, 438 U.S. 265 (1978) (holding that race-sensitive policies do not violate the Fourteenth Amendment's Equal Protection Clause).

Today, however, African American and Hispanic (minority) students are still underrepresented in higher education and graduate at lower rates than their nonminority counterparts (Figures 1 and 2).[1] Critics have advanced the hypothesis that affirmative action programs can hurt their intended beneficiaries by causing them to enroll in institutions for which they are underprepared. Minorities who are "overmatched" subsequently graduate at lower rates than they would have if they had matriculated at less-selective institutions that better matched their academic credentials. This is known as the "mismatch hypothesis."

[1] Throughout this paper, I use the term "minority" to refer to African American and Hispanic students because these two racial groups are classified as "historically underrepresented minorities" by the University of California, University of Texas, and other institutions of higher-education. This terminology is consistent with Card and Kruger (2005), Loury and Garman (1993, 1995), Hinrichs (2012, 2014), and Hill (2017).

Figure 1: Graduation Rate Distributions by Racial Group

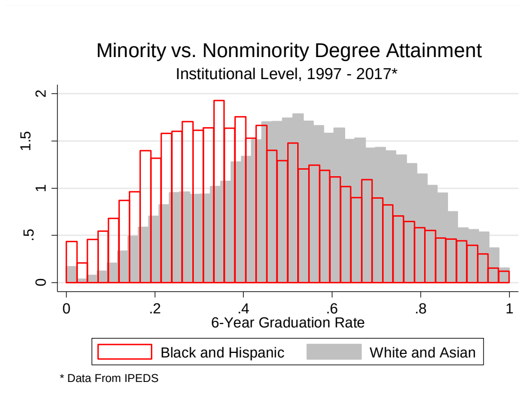
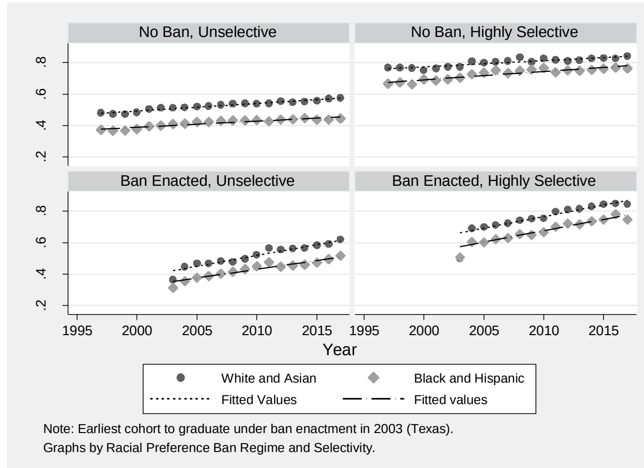


Figure 2: Graduation Rates by Ban Regime and College Selectivity



Since *Bakke*, several states have enacted – via voter initiative or judicial fiat – statewide bans on the use of racial preferences in admissions decisions. Table 1 shows the development and (at times) declension of statewide affirmative action bans in the United States. Strikingly, these racial preference rollbacks seem to effectuate haphazardly across space and time. I exploit this quasi-experimental, plausibly exogenous variation in racial preference ban adoption to inform the contentious public policy debate on affirmative action.

This paper endeavors to empirically evaluate the mismatch hypothesis by identifying the causal impact of affirmative action bans on minority graduation rates over a twenty-year period. To the extent statewide affirmative action bans vary across space and time, they allow for the study of affirmative action programs using a difference-in-difference framework. If the mismatch hypothesis is correct, racial preference bans should alleviate overmatch effects and increase minority graduation rates. An alternative hypothesis posits that affirmative action helps propel minorities into higher quality colleges where graduating within four years is the expectation and the norm. If these "college quality" effects dominate, minority graduation rates should decrease after statewide racial preference bans.

Table 1: Affirmative Action Bans and Percentage Plans by State

State \ Year	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Texas[2]	X	X,T	X,T	X,T	X,T	X,T	X,T	T	T,A	T,A	T,A	T,A	T,A	T,A	T,A	T,A	T,A	T,A
California[3]		X	X	X	X,T	X,T	X,T	X,T	X,T	X,T	X,T	X,T	X,T	X,T	X,T	X,T	X,T	X,T
Washington			X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Florida[4]					X,T	X,T	X,T	X,T	X,T	X,T	X,T	X,T	X,T	X,T	X,T	X,T	X,T	X,T
Georgia[5]						X	X	X	X	X	X	X	X	X	X	X	X	X
Michigan[6]										X	X	X	X	X	?	?	?	X
Nebraska												X	X	X	X	X	X	X
Arizona														X	X	X	X	X
New Hampshire																X	X	X
Oklahoma																	X	X

Key: **X** = Affirmative action ban; **T** = "Top-X" percent guaranteed admissions program; **?** = Uncertainty due to ban enacted but ruled unconstitutional, but ban later reinstated; **A** = Affirmative action program reintroduced after ban ruled unconstitutional and not later reinstated

This paper follows the work of Hill (2017), Hinrichs (2012, 2014), and Backes (2012) in examining the aggregate effect of affirmative action bans using a difference-in-difference approach. However, this paper examines the effect of racial preference bans on minority graduation rates instead of enrollment and is the first to disaggregate mismatch effects by major category and college selectivity on a national scale. This is important because no previous literature has ascertained whether mismatch is confined to STEM majors at highly selective institutions.[7]

[2] Ban established by *Hopwood v. Texas,* 78 F.3d 932 (5th Cir. 1996). Overturned by the Supreme Court's decisions in *Grutter v. Bollinger,* 539 U.S. 306 (2003), and *Gratz v. Bollinger,* 539 U.S. 306 (2003). The University of Texas at Austin reintroduced affirmative action for its fall 2005 admissions cycle. Texas House Bill 588 guaranteed admission to a public campus of the student's choice for the top 10% of any high school class.
[3] Following the enactment of Proposition 209, a voter initiative, California banned affirmative action starting with the 1998 entering class. In 2001, it implemented an "Eligibility in the Local Context Program," which guaranteed admission to a University of California (UC) campus for the top 12.5% of California public high school graduates. This number was later reduced down to 9% and other requirements were added.
[4] Governor Jeb Bush banned the use of racial preferences in admissions decisions and established the "Talented 20" guaranteed-admissions program in his *One Florida Initiative* (Executive Order 99-281, 1999).
[5] Only affecting the University of Georgia.
[6] *Gratz* and *Grutter* disallowed the use of a "points system" to boost minority enrollment at the University of Michigan. Michigan voters then passed the Michigan Civil Rights Initiative (Proposal 2), amending the Michigan Constitution to ban affirmative action in 2006. The proposal was ruled unconstitutional by the Sixth Circuit Court of Appeals in 2011. However, in April 2014 the Supreme Court reversed the Sixth Circuit and reinstated the ban in *Schuette v. Coalition to Defend Affirmative Action,* 572 U.S. 291 (2014). This case established the legal right of states to ban affirmative action in public universities.
[7] Hill (2017), Backes (2012), and Hinrichs (2012) find that affirmative action bans decrease minority enrollment but are unable to disentangle mismatch and college quality effects. Hill (2017) confines his analyze to STEM majors and Hinrichs (2012) disaggregated by college selectivity, but neither disaggregates results by both college selectivity and major category.

Using a comprehensive sample of institutions, I examine whether affirmative action rollbacks increase minority graduation rates and in what major categories (if any) are mismatch effects prevalent. My results suggest that racial preference bans increase minority graduation rates at highly selective public colleges, corroborating Arcidiacono et. al (2014), Loury and Garman (1993, 1995), Hinrichs (2014), and Sowell (2004) on a national scale. However, my results diverge from Cortes (2010) and Hill (2017). Interestingly, my results suggest that mismatch effects are not confined to STEM fields – they are present in the Social Sciences as well, albeit to a lesser extent. These results are robust to the inclusion of private colleges and affirmed by the construction of synthetic control states.

The rest of this paper proceeds as follows: Section 2 reviews the previous empirical literature on mismatch, Section 3 describes the data source used, Section 4 presents this paper's empirical strategy, Section 5 reveals results, Section 6 probes robustness, and Section 7 concludes.

2. Literature Review

Only the top 20 to 30 percent of four-year colleges use racial preferences in admissions decisions, as most schools simply are not selective enough to afford the use of affirmative action programs (Bowen and Bok, 1998; Kane, 1998; Arcidiacono, 2005). Within these selective colleges, there is a substantial gap in academic preparation between minority and nonminority matriculants (Baker, 2019). Minorities frequently and persistently graduate at lower rates than their nonminority counterparts (Figure 2).

Affirmative action policies can impact minority graduation rates through two distinct mechanisms. The mismatch hypothesis predicts that banning affirmative action could better match students to the institutions where they enroll, thereby increasing minority college graduation rates.

However, an expanding literature suggests that college quality and collegiate resources each exert a separate influence on degree completions independent of mismatch effects. Bound and Turner (2007) developed the insight that college resources are relatively inelastic and do not respond *pari passu* to short-run demand shocks in enrollment. They use Census data on the size of each "birth cohort" in a state for a particular graduating class as an instrument for enrollment demand and discover that graduation rates are strongly negatively correlated with the size of the birth cohort. This finding, which the authors term "cohort crowding," indicates that collegiate resources matter for degree attainment.

Loury and Garman (1993, 1995) conducted some of the earliest studies on mismatch. Using data from the National Longitudinal Survey of the Class of 1972, Loury and Garman (1993) used a selection-on-observables approach and find that some students attending the most selective colleges would have higher earnings if they had attended less selective schools. They interpret their findings as evidence for "mismatch effects" and inaugurated the term into the economics literature. Light and Strayer (2000) extend this work by estimating graduation rates based on performance on Armed Forces Qualification Test (AFQT) using a multinomial probit model. They find that graduation rates deteriorate monotonically among the bottom 25% of test-takers as college quality increases. For those that score higher on the AFQT, the trend largely reverses. These findings suggest that policies inducing low-ability students to attend higher-quality schools are counterproductive in terms of graduation.

There is no consensus in the literature about the effects of racial preference bans on minority degree attainment. Researchers using a difference-in-difference approach have reached different conclusions with different datasets.[8] Hinrichs (2012) uses American Community Survey data and finds that affirmative action does not impact the average student, but minority students "cascade down" from more selective schools to less selective ones as a result of racial preference bans. Hinrichs (2014) conducted follow-up studies using data from the Integrated Postsecondary Education Data System (IPEDS) and found that racial preference bans have no effect on minority graduation rates. Cortes (2010) examined the effect of affirmative action bans in Texas using micro-level data from a sample of public and private universities. She finds that affirmative action bans decrease minority six-year graduation rates by 2.7 to 4.0 percentage points. This would indicate that college-quality effects dominate mismatch effects.[9] Arcidiacono et. al (2014) examined the effects of Proposition 209 in California using confidential micro-data from the University of California (UCOP data). They find that California's statewide affirmative action ban caused minority graduation rates to increase by 4 percentage points.

Affirmative action bans may not be exogenous shocks to racial preferences in undergraduate admissions. For instance, eliminating affirmative action may change applicants' behavior. Affirmative action bans may make minorities feel unwelcome and dissuade them from applying to college, or it may induce minority applications if minorities believe the signaling value of a college degree increases after racial preference bans.[10] However, Card and Krueger (2005), using a difference-in-difference estimation strategy and confidential micro-data from California

[8] It may be the case that college-quality and mismatch effects are equal in strength and generally offset each other, as Arcidiacono and Lovenheim (2016) and Dillon and Smith (2017) argue.
[9] However, Cortes finds that the decline can be explained in part by the "Texas Top 10 Percent" guaranteed admissions rule, which more likely impacted top-decile students unaffected by the ban than drove down completion rates for lower-ranked students.
[10] In *Affirmative Action Around the World*, Thomas Sowell examines the implementation of affirmative action in other countries, such as India, where admissions are based only on observed factors such as test scores. Using four different case studies, Sowell finds that affirmative action bans may induce "[t]he redesignation of individuals and groups, in order to receive the benefits of preferences and quotas intended for others" (Sowell 2004, 190).

and Texas, find no change in minority SAT score-sending behavior (which they use as a proxy for minority application patterns) after affirmative action bans. A related issue is that minority students may be transferring from "more difficult" majors (such as STEM) to "less difficult" ones (such as the humanities) following admission to selective colleges for which they are underprepared.[11] To address this concern, Hill (2017) uses a difference-in-difference model and IPEDS data to examine the effect of racial preference bans on minority degree completions in STEM fields only. Hill finds that affirmative action bans did not significantly decrease the number of minority STEM graduates at highly selective colleges. However, Hill examines neither minority graduation rates nor fields other than STEM. In addition, Arcidiacono and Lovenheim (2016) uses UCOP data to determine that minorities in STEM at UC Berkeley and UCLA with less academic preparation than their peers would have higher graduation rates if they had attended a less selective UC campus.

This paper relies on methodological guidance from Hill (2017), Hinrichs (2012, 2014), and Backes (2012) in examining the aggregate effect of affirmative action bans on minority graduation rates using a difference-in-difference approach. This paper is the first to distinguish between STEM and non-STEM majors as well as between selective and unselective colleges at the national level using a 1997-2017 dataset.

3. Data

The data for this paper comes from IPEDS by the National Center for Education Statistics (NCES). The IPEDS database encompasses all Title IV institutions in the United States and provides rich data on each institution from 1997 to 2017. As mandated by the Higher Education Act of 1965, IPEDS reports cohort graduation rates for all full-time, first-time students at

[11] For example, Arcidiacono et. al (2012) find that Blacks have lower persistence rates in the Natural Sciences, Mathematics, Engineering, and Economics than Whites, and Blacks with initial interest in these fields are more likely to switch to majors in the humanities or social sciences.

institutions where students receive federal student aid. I drop all institutions without data across all years in the sample (such as UC Merced, established in 2005).[12] The full sample is a balanced panel dataset. Initially, only public four-year colleges are included in the sample. Private four-year colleges unaffected by affirmative action bans are later reinstated as an additional control group for a robustness check. For accounting purposes, summary statistics detailing sample and subsample sizes (by number of institutions and selectivity) are presented in Table 2 below. This paper uses aggregate data from IPEDS and thereby treats the university as the unit of observation.

Table 2: Institutional Level Descriptive Statistics by Selectivity

Panel A: *Public Institutions*		Non-Ban States				Ban States			
	All Institutions	All Institutions	Highly Selective	Moderately Selective	Unselective	All Institutions	Highly Selective	Moderately Selective	Unselective
Institutions	499	407	29	33	345	92	17	14	61
	Number of Observations:					10479			
Panel B: *Public and Private Institutions*		Non-Ban States				Ban States			
	All Institutions	All Institutions	Highly Selective	Moderately Selective	Unselective	All Institutions	Highly Selective	Moderately Selective	Unselective
Institutions	1360	1122	99	94	929	238	26	33	179
	Number of Observations:					28,560			

Notes: Number of public four-year institutions in each respective sample and subsample. Racial preferences used only at the top 20% of institutions in the United States (Bowen and Bok, 1998; Arcidiacono, 2005). Accordingly, "Highly Selective" institutions are defined as those within the top decile of admissions selectivity, "Moderately Selective" institutions are those between the tenth and twentieth percentile, and "Unselective" institutions are those in the bottom eighty percent of undergraduate admission rates.

Figure 2 graphs six-year graduation rates for minorities and nonminorities under ban and nonban regimes by admissions selectivity. Following methodological guidance from Hinrichs (2014, 48), I examine six-year instead of four-year graduation rates because "many students who graduate do not graduate in four years," and "many students graduate in six years." Students at

[12] I also drop historically black colleges and universities and all institutions where enrollment numbers by racial group do not sum to overall enrollment. In models restricted to public institutions, I drop all institutions that are not coded as four-year public institutions in every year of the sample.

selective institutions graduate at higher rates than their peers at less selective schools. The gap between minority and nonminority graduation rates remains roughly constant across time in all four panels; minority students consistently graduate at lower rates than their nonminority counterparts, but graduation rates trended upwards at a slightly faster rate for minority students in ban states vis-à-vis nonban states. The gap between minority and nonminority graduation rates is larger at unselective institutions in nonban states than selective institutions in nonban states.[13]

A potential limitation of the IPEDS database is that the NCES only surveys institutions where students receive federal student aid (e.g., Federal Pell Grants, Perkins Loans, Ford Direct Student Loans, etc.). However, this group includes most institutions in the United States, since around two-thirds of all college and university students receive federal student aid (NCES, 2015-16). According to the NCES, more than 7,500 institutions complete IPEDS surveys each year, including "research universities, state colleges and universities, private religious and liberal arts colleges, [and] for-profit institutions."[14] Moreover, some non-Title-IV institutions voluntarily report data to IPEDS. Another limitation of the IPEDS database is that IPEDS includes only first-time, full-time students enrolled in a degree program. This omits a sizable share of the population currently attending college, but still encompasses most students affected by affirmative action programs (Hinrichs, 2014, 46). As shown in Table 2, the full sample follows over two hundred private and public institutions in ban states and over one-thousand institutions in nonban states over twenty years, amounting to over twenty-thousand observations.

[13] Table 6 in the Appendix reports descriptive statistics of the entire sample for variables used in the regression specifications below. Further descriptive statistics disaggregated by subsample and the major-classification scheme used by the College Board are presented in Tables 7 and 8.
[14] "About IPEDS." (2020, May 1). Retrieved from https://nces.ed.gov/ipeds/about-ipeds

4. Model and Empirical Strategy

The effect of a statewide affirmative action ban for each racial group at public university *i* in state *s* in year *t* is estimated using the following difference-in-difference model:

$$g_{ist} = \sum_{j=1}^{3} \beta_j \left(ban_{s,t-6} \times Sel_j\right) + \sum_{j=1}^{3} \delta_j \left(year_t \times Sel_j\right) + u_i + \eta_s t + \varepsilon_{ist} \qquad (1)$$

The dependent variable *g* is graduation rates within 150% of normal time (6 years). The independent variable *ban* is a binary variable indicating whether state *s* has banned affirmative action by the time of enrollment in year *t*, u_i are university level fixed effects, $\eta_s t$ are linear state-level graduation rate trends, ε_{sit} is a disturbance, and β_j is the parameter of interest.[15] This specification includes year-by-selectivity fixed effects $year_t \times Sel_j$, where *Sel* codes for selectivity and j ∈ *{1, 2, 3}*, corresponding to highly selective (1), moderately selective (2), and unselective (3) colleges. The treated group is comprised of institutions under ban regimes in applicable ban states, and the control group is comprised of public institutions in nonban states.

Cortes (2010), Long (2004), and Hinrichs (2014) show that percentage plan (top-x) programs designed in response to – and intended to ameliorate the negative effects of – racial preference bans impact minority graduate rates. Additionally, statewide politics may affect the minority college search and application process prior to matriculation and graduation. For example, statewide affirmative action bans may make minorities feel unwelcome and thereby deter them from applying to selective colleges. Hence, equation (2) introduces unique regressors controlling for a "ban discussion period" and whether an affirmative action ban was enacted by voter initiative (as opposed to a court decision or executive action).[16] The ban discussion period dummy controls

[15] The variable *ban* is the product of two dummy variables: *ban* = *Ban_Enactment* * *After*

[16] The affirmative action ban discussion period is defined as the length of time in between either of the following two events and the enactment of the ban: (1) the commencement of petition-gathering for a voter initiative, or (2) initial filings in litigation that would eventually arise in a court decision that bans affirmative action. For example: in

for the duration and timing of a period in which discussion of an affirmative action ban was potentially present in the discourse surrounding racial justice or educational policy in a state. The main insight of this specification is that statewide political rhetoric affects minority graduation rates. A model controlling for "top-x" percent programs, "ban-discussion" periods, and whether the ban was implemented by a voter initiative is:

$$g_{ist} = \sum_{j=1}^{3} \beta_j \left(ban_{s,t-6} \times Sel_j\right) + \sum_{j=1}^{3} \gamma_j \left(topX_{s,t-6} \times Sel_j\right) + \sum_{j=1}^{3} \delta_j \left(year_t \times Sel_j\right) + \sum_{j=1}^{3} \phi_j \left(d_{s(t-\lambda)} \times Sel_j\right) + v_{st} + u_i + \eta_s t + \varepsilon_{ist} \quad (2)$$

In this specification, *topX* is a dummy variable indicating whether state *s* had implemented a percentage plan guaranteed admissions program at the time of enrollment. The binary variable *v* indicates whether there was an affirmative action ban implemented as a result of a voter-led initiative in state *s* at in year *t*. This is not the case in Texas and Georgia, where an affirmative action ban was implemented by the *Hopwood* decision, and Florida, where it was implemented by executive action. The variable d denotes whether discussion of a statewide affirmative action ban was in the statewide political discourse in the λ years preceding the ban. For equations (1) and (2): if the mismatch hypothesis is correct, then, *ceteris paribus*, $\frac{\partial g_{ist}}{\partial_{ban}} = \beta_j > 0$. If college quality effects dominate, then, all else equal, $\frac{\partial g_{ist}}{\partial_{ban}} = \beta_j < 0$.

California, the UC Regents discussed the idea of an affirmative action ban from 1996 to 1998, when a rollback was enacted via Proposition 206 – hence the ban discussion period is between 1996 and 1998. In Texas, litigation that would eventually arise in *Hopwood* commenced in 1994, the Fifth Circuit issued its opinion 1996, and the Supreme Court denied certiorari that same year. Hence, the Texas ban discussion period is from 1994 to 1996. Executive actions initiated unilaterally by a state governor are assumed to have a 1-year discussion period.

5. Results

5.1. Effects of Bans on Overall Graduation Rates

Table 3 presents results from specifications (1) and (2). At selective public institutions in specification (2), affirmative action bans increase minority but do not change nonminority graduation rates, consistent with the mismatch hypothesis. Without controls, the effect is not statistically significant for Hispanics at the 95% confidence level. Holding all else constant, racial preference bans are predicted to increase Black graduation rates by 3.7 percentage points and Hispanic graduation rates by 5.2 percentage points on average. Results are statistically significant at the 95% confidence level. It is notable that mismatch effects are only significant at the most selective postsecondary institutions in the United States.

Table 3: Effect of Affirmative Action Bans on Degree Attainment Rates by Racial Group, Public Only

Specification: Variables and Controls	All	Racial Group (1) White	Asian	Black	Hispanic	(2) White	Asian	Black	Hispanic
Ban × Highly Selective	0.0194 (0.0120)	-0.00398 (0.0110)	0.0149 (0.0232)	0.0429*** (0.00914)	0.0406* (0.0227)	-0.00776 (0.00678)	0.00763 (0.0168)	0.0365** (0.0147)	0.0519** (0.0221)
Ban × Moderately Selective	0.00654 (0.0164)	-0.00528 (0.0193)	0.0293 (0.0408)	0.0273 (0.0213)	0.0182 (0.0256)	0.00658 (0.0164)	0.0482 (0.0390)	0.0508 (0.0315)	0.0335* (0.0175)
Ban × Unselective	-0.00463 (0.00398)	-0.00797 (0.00521)	0.00661 (0.0116)	-0.000983 (0.00686)	0.00466 (0.00427)	-0.00822 (0.00496)	0.00384 (0.00753)	0.00286 (0.00733)	0.0118 (0.0115)
State Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Percentage Plan Controls	Yes	No	No	No	No	Yes	Yes	Yes	Yes
Voter Initiative Controls	Yes	No	No	No	No	Yes	Yes	Yes	Yes
Discussion Period Controls	Yes	No	No	No	No	Yes	Yes	Yes	Yes
R-Squared	0.411	0.224	0.069	0.111	0.080	0.356	0.080	0.116	0.089
Number of Observations					10,479				
Number of Institutions					499				

Notes: Robust standard errors are in parentheses. The dependent variable is graduation rates by racial group and institutional selectivity after affirmative action bans. Year-by-selectivity and institution fixed effects are absorbed for all specifications. “Highly Selective” institutions are defined as those in the top 10% of selectivity by undergraduate admission rates, “Moderately Selective” as those in the top 10-20%, and “Unselective” in the bottom 80%. Specification (1) lacks ban-related controls, specification (2) includes these controls. *** p<0.01, ** p<0.05, * p<0.1

Affirmative action bans have no statistically significant impact on minority or nonminority graduation rates at moderately selective or unselective colleges at the 95% confidence level. This affirms previous empirical findings that only selective institutions can “afford” to practice affirmative action. The inclusion of controls pertaining to potential latent effects of racial preference bans on minorities beyond the use of racial preferences in admissions decisions – whether a ban was implemented as a result of a voter initiative and the length of a "ban discussion" period prior to ban enactment – does not change the sign of the estimate but increases its power for Hispanics. However, these controls reduce the estimated size of mismatch effects by 0.6 percentage points for African Americans and increase the estimated size of mismatch effects by 1.1 percentage points for Hispanics, suggesting that Percentage Plan, Voter Initiative, and Ban Discussion effects explain some of the variation in minority graduation rates. Gubernatorial or statewide political rhetoric matters, for instance, if affirmative action bans embody a general shift in racial attitudes within a particular state that manifests in ways other than affirmative action bans, such as hostile attitudes towards minorities that dissuades them from applying to selective intuitions or makes them feel unwelcome upon matriculation. These controls do not significantly change the estimators for White and Asian graduation rates.

5.2. Effect of Affirmative Action Ban on Graduation Rates by Major

The effect of affirmative action bans on minority and nonminority graduation rates by major categories are shown in Table 4 (Panels A – G). These results show that mismatch effects are strongest in STEM, but also significant (although effects are smaller) in the social sciences. Affirmative action bans increase Black and Hispanic six-year graduation rates by around two-to-three percentage points in STEM and one-to-two percentage points in the social sciences. There are many spurious results in the "wrong direction" that are statistically significant but not economically meaningful, potentially due to very low sample sizes in some fields. Overall, my results do not support the hypothesis that mismatch effects, if present, are confined only to STEM majors. Intuitively, this means that minority students may have lower persistence rates in the sciences and social sciences vis-à-vis nonminorities, as Arcidiacono et. al (2012) estimate.

Table 4: Effect of Racial Preference Ban on Graduation Rates by Race, Selectivity, and Major Category

Interaction	Racial Group				
	All	White	Asian	Black	Hispanic
	Panel A: Arts and Humanities				
Ban × Highly Selective	0.00118	-0.00285	-0.000684	-0.00291	-0.00163
	(0.00488)	(0.00504)	(0.00438)	(0.00861)	(0.00893)
Ban × Moderately Selective	-0.00296	-0.00400	-0.00169	0.000476	-0.00175
	(0.00491)	(0.00491)	(0.00488)	(0.00386)	(0.00470)
Ban × Unselective	0.000433	0.000161	0.00130	-0.00140**	-0.00108
	(0.00129)	(0.00147)	(0.00111)	(0.000644)	(0.000988)
	Panel B: Business				
Ban × Highly Selective	-0.00609	-0.00977	-0.0109	-0.00666	-0.00133
	(0.00823)	(0.00728)	(0.00805)	(0.00541)	(0.00823)
Ban × Moderately Selective	0.00674	0.00462	0.0134	0.00580	0.00705
	(0.00546)	(0.00637)	(0.0114)	(0.00629)	(0.00432)
Ban × Unselective	0.000975	0.000382	0.00392**	0.00139	0.00289
	(0.00123)	(0.00132)	(0.00183)	(0.00279)	(0.00173)
	Panel C: Health and Medicine				
Ban × Highly Selective	0.000732	-0.000310	0.00228	0.00306	0.00383
	(0.00427)	(0.00428)	(0.00499)	(0.00314)	(0.00522)
Ban × Moderately Selective	0.00468***	0.00507***	0.00881***	0.00594**	0.00665***
	(0.00161)	(0.00145)	(0.00262)	(0.00280)	(0.00216)
Ban × Unselective	-0.000796	-0.00117	-0.000905	0.000893	-0.000314
	(0.00138)	(0.00147)	(0.00130)	(0.00155)	(0.00124)
	Panel D: Multi-/Interdisciplinary Studies				
Ban × Highly Selective	0.000780	-0.00391	-0.00328	0.00797***	0.00232
	(0.00625)	(0.00711)	(0.00845)	(0.00276)	(0.00784)
Ban × Moderately Selective	0.00208	0.00319	0.0135**	0.00889**	0.00133
	(0.00372)	(0.00419)	(0.00585)	(0.00394)	(0.00592)
Ban × Unselective	0.00874***	0.00818***	0.0103***	0.00785***	0.00873**
	(0.00137)	(0.00135)	(0.00204)	(0.00151)	(0.00348)
	Panel E: Public and Social Services				
Ban × Highly Selective	-0.00178*	-0.00332**	-0.00172	-0.00254	-0.00411**
	(0.000985)	(0.00154)	(0.00146)	(0.00176)	(0.00167)
Ban × Moderately Selective	0.00229	0.00173	0.00373	0.000830	-0.000405
	(0.00238)	(0.00252)	(0.00237)	(0.00165)	(0.00207)
Ban × Unselective	-0.000353	-0.000469	-0.000122	-0.00144**	-0.00268***
	(0.00106)	(0.000998)	(0.000631)	(0.000609)	(0.000654)
	Panel F: Science, Math, and Technology				
Ban × Highly Selective	0.0223	0.0170	0.0193***	0.0255**	0.0350***
	(0.05566)	(0.06007)	(0.00655)	(0.0112)	(0.00659)
Ban × Moderately Selective	0.00473	0.00264	0.0104	0.0184	0.0125
	(0.0114)	(0.0118)	(0.0163)	(0.0128)	(0.00994)
Ban × Unselective	-0.00383**	-0.00440***	-0.00432	-0.00224	0.00296
	(0.00159)	(0.00163)	(0.00333)	(0.00231)	(0.00291)
	Panel G: Social Sciences				
Ban × Highly Selective	-0.00154	-0.00439	0.00262	0.0123***	0.0177**
	(0.00692)	(0.00582)	(0.00784)	(0.00351)	(0.00768)
Ban × Moderately Selective	-0.00634	-0.00793	-0.00154	0.00970	0.00723
	(0.00716)	(0.00693)	(0.00826)	(0.0115)	(0.00780)
Ban × Unselective	-0.00954***	-0.0106***	-0.00612*	-0.00187	0.00159
Number of Observations			10,479		
Number of Institutions			499		

Notes: Robust standard errors in parentheses. All specifications include State Trends, Percentage Plan, Voter Initiative, and Discussion Period controls. "Highly Selective" institutions are defined as those in the top 10% of selectivity by undergraduate admission rates, "Moderately Selective" as those in the top 10-20%, and "Unselective" in the bottom 80%. *** p<0.01, ** p<0.05, * p<0.1.

6. Robustness

For β_j to capture the causal effect of affirmative action bans on minority graduation rates, the critical assumption in Equation (2) is that in absence of racial preference bans the average change in degree attainment rates would have been the same between institutions under ban and nonban affirmative action regimes. This is termed the "parallel trends" assumption. If the parallel trends assumption holds, treated and nontreated institutions will not exhibit materially differing time trends, implying that γ_j, δ_j, ϕ_j, and η_s capture secular time trends affecting universities under ban and nonban affirmative action regimes. This paper probes the robustness of the difference-in-difference estimation strategy using a synthetic control approach and a triple-difference estimation technique.

6.1. Synthetic Control

Following Abadie et al. (2010), I estimate a model in which an affirmative action ban (the treatment) effectuates at some point in time for a certain state but not in the pool of potential control states. I specify a vector of controls, and a "synthetic" control state is constructed whereby the convex combination of the potential control units most closely matches the treatment unit value of these variables. The synthetic control approach allows me to project graduation rates in the synthetic control into a counterfactual posttreatment period that approximates what would have happened to graduation rates in a state that had banned affirmative action if the affirmative action ban not gone into effect (Hinrichs, 2012). The synthetic control model is therefore:

$$g_{st}(0) = \sum_{j=2}^{J+1} w_j g_{jt} \tag{3}$$

Where $\mathbf{W} = (w_2, w_3, \ldots, w_{J+1})'$, with $w_2 + w_3 + \ldots + w_{J+1} = 1$. Each value of $\mathbf{W}$ represents a potential synthetic control. The objective is to select weights $\mathbf{W}$ such that $\|\boldsymbol{X}_1 - \boldsymbol{X}_0\boldsymbol{W}\|$ is minimized, where $\mathbf{X}_1$ is a vector of pretreatment predictors, and $\mathbf{X}_0$ is the same set of predictors for the control units. I include institutional enrollment, family income, share of female students, average SAT scores, share of first-generation students, undergraduate admission rates, and four-year transfer rates in my set of predictors. I then choose matrix $\mathbf{V}$ such that I minimize $\sqrt{(\boldsymbol{X}_1 - \boldsymbol{X}_0\boldsymbol{W})'\boldsymbol{V}(\boldsymbol{X}_1 - \boldsymbol{X}_0\boldsymbol{W})}$. The matrix $\mathbf{V}$ weights the variables used in synthesizing by minimizing the mean-squared predicted error in the entire pretreatment period.

For illustrative purposes, I present results from California below. Figure 3 shows that racial preference bans increased minority graduation rates at highly selective public universities in California, but Figure 4 shows no significant effects for nonminorities. The increase in minority graduation rates from better matching is similar to what is predicted in specification (2).[17]

Figure 3 - Ban Effects on Californian Minorities
Black and Hispanic, Highly Selective

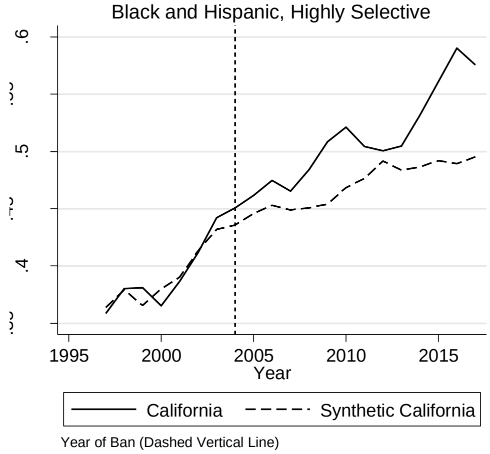
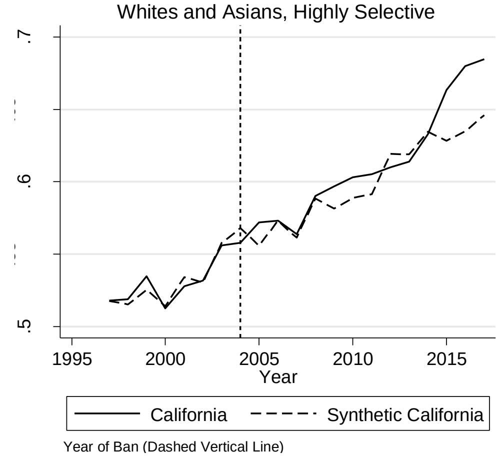


Figure 4 - Ban Effects on Californian Nonminorities
Whites and Asians, Highly Selective



6.2. Triple-difference

As an additional robustness check, I reinstitute private colleges into the sample as an additional control group to construct a difference-in-difference-in-difference (triple-difference) model. The regression specifications presented in (1) and (2) may conceal how certain public universities are more affected by affirmative action bans than others. Comparing graduation rates

[17] Results for Moderately Selective or Unselective institutions, whether in California or in other states, appear very similar to what is shown in Figure 4.

at public universities in these ban states with public universities in states that have not banned affirmative action creates a potential complication: other factors unrelated to affirmative action bans may systemically vary across states. For example, nonban states may fund higher education less generously than ban states, or vice versa. Another approach compares public and private institutions (unaffected by statewide affirmative action bans) in ban states. The potential problem with this approach is that other factors unrelated to a newly implemented affirmative action ban may affect minority graduation rates differently at public universities vis-à-vis private ones. For example, private universities may consider "legacy" factors in admissions decisions while public universities might devalue or disregard nepotistic relationships. A more robust specification than either model could be obtained by using both a different state and different control type. This is the triple-difference estimation strategy. The model is therefore:

$$g_{ist} = \sum_{j=1}^{3} \beta_j \left(ban_{s,t-6} \times Sel_j \times Priv \right) + \sum_{j=1}^{3} \gamma_j \left(topX_{s,t-6} \times Sel_j \times Priv \right) + \sum_{j=1}^{3} \delta_j \left(year_t \times Sel_j \times Priv \right) + \sum_{j=1}^{3} \phi_j \left(d_{s(t-\lambda)} \times Sel_j \times Priv \right) + v_{st} + u_i + \eta_s t + \varepsilon_{ist} \tag{4}$$

Where $Priv$ is a binary variable indicating whether a university is coded as a private for-profit or private nonprofit institution across all years in the sample.

Overall, the triple-difference analysis tends to support the results of specifications 1 and 2. Table 5 presents the triple-difference results from equation (4). Results are consistent with the mismatch hypothesis, though the increase in graduation rates is 0.71 and 1.11 percentage points lower for Blacks and Hispanics, respectively, vis-à-vis specification (2) in Table 3, but results are still significant at the 95% confidence level. Compared to Table 3, the power of the estimate increases for Blacks. Notably, mismatch effects can also be detected at moderately selective institutions (that is – those between the first and second decile of selectivity).

Table 5 – Effect of Affirmative Action Ban on Minority Graduation Rates - Triple-difference Analysis

Variables	All Students	Racial Group			
		White	Asian	Black	Hispanic
Ban × Highly Selective × Private	0.0123	-0.00789	0.00731	0.0294***	0.0408**
	(0.0118)	(0.0135)	(0.0218)	(0.00934)	(0.0159)
Ban × Moderately Selective × Private	0.0185*	0.0120	0.0562	0.0500**	0.0407***
	(0.0105)	(0.0104)	(0.0360)	(0.0243)	(0.0147)
Ban × Unselective × Private	-0.00478	-0.00956	0.00697	-0.00935	-0.000672
	(0.00977)	(0.00941)	(0.00728)	(0.0114)	(0.00774)
Constant	-6.847***	-7.845***	-10.52***	-6.589***	-8.897***
	(0.320)	(0.395)	(1.069)	(0.786)	(0.927)
R-squared	0.125	0.118	0.032	0.035	0.034
Number of Observations	28, 560				
Number of Institutions	1,360				

Notes: Robust standard errors in parentheses. State Trends, Percentage Plan, Voter Initiative, and Discussion Period controls are added in each regressive specification. “Highly Selective” institutions are defined as those in the top 10% of selectivity by undergraduate admission rates, “Moderately Selective” as those in the top 10-20%, and “Unselective” in the bottom 80%. *** p<0.01, ** p<0.05, * p<0.1.

7. Conclusion

My findings suggest that minority graduation rates significantly increase after racial preference bans at highly selective public institutions, indicative of mismatch dominating college-quality effects. In addition to STEM, mismatch effects are present, albeit to a lesser extent, in the social sciences as well. These results are robust to the inclusion of private institutions and affirmed by a synthetic control approach.[18] These results are consistent with those of Hinrichs (2014) and Arcidiacono et. al (2014), who uses only UCOP data. My findings are not inconsistent with Hinrichs (2012, 719), who finds that “affirmative action bans have no effect” for the “typical student at the typical college” even though affirmative action programs may cause some students to “cascade down” the selectivity ladder. Only a small fraction of public colleges in ban states in

[18] These results diverge from Cortes (2010) – who also controls for percentage plan programs implemented in response to affirmative action bans – but Cortes restricts her sample to the state of Texas and does not distinguish colleges by selectivity.

ban years are highly selective, and I find no evidence of significant mismatch effects at unselective institutions, encompassing roughly 80% of the sample.

In their review of the literature, Arcidiacono, Lovenheim, and Zhu (2015) articulated the empirical challenge of disentangling mismatch and college quality effects.[19] My work joins Hill (2017), Hinrichs (2012, 2014), Arcidiacono et. al (2014) in answering this challenge. However, this paper is the first to find evidence for mismatch effects across two decades of IPEDS data at highly selective institutions. Moreover, no previous literature has examined whether mismatch effects are confined to a single major category at this nationwide scale. In finding that mismatch effects are present only at highly selective institutions and not confined only to STEM fields, my paper fills an important void in the literature.

However, I must present these findings with two caveats. First, it is still possible that (particularly biracial) minorities may change their race reporting behavior in response to racial preference bans.[20] Nevertheless, it is unclear whether and how a disinclination to report oneself as a minority after affirmative action is banned impacts the graduation rates of those who continue to self-identify as Black or Hispanic. Hill (2017) found that statewide affirmative action bans does not change the percentage of “race unknown” students in the IPEDS database. Additionally, Card and Kruger (2005) found no change in minority race-reporting behavior after affirmative action bans using SAT score-sending behavior as a proxy for minority interest.

A more serious challenge to my interpretation stems from the fact that colleges and universities may themselves respond to affirmative action bans by investing more in minority

[19] Which, they note, Bound and Turner (2007) were unable to do.
[20] Again, Sowell (2004) suggests that some nonminorities may be encouraged to “redesignate” themselves as minorities following the enactment of race-sensitive admissions policies.

students following an inability to employ racial preferences in admissions decisions.[21] For example, institutions may more aggressively implement special tutoring, support, guidance, or mentoring services targeted at or restricted to minority students after affirmative action is banned, which could increase minority graduation rates after a ban. In this case, collegiate responses, rather than mismatch, could account for the increasing minority graduation rates post-ban. Unfortunately, there is no good data in IPEDS to control for collegiate responses to affirmative action bans, which, I submit, may be a significant source of endogenous variation. One could control for this endogenous variation by extracting textual data from cached university websites describing targeted minority tutoring or support services (by year) and quantifying the extent to which universities help minorities more after racial preferences are banned. This is beyond my level of technical expertise, and public data on intra-university student support services may not even be available. Regardless, university responses to affirmative action bans could prove a fruitful direction for future research.

The superheated public-policy debate surrounding the use of racial preferences in admissions decisions will continue.[22] If there exists a racial imbalance in degree attainment rates, colleges and universities are prone to attempt corrective steps. However, this paper finds evidence that affirmative action programs may harm some of its intended beneficiaries. These results should not be taken as a larger indictment of affirmative action programs in general, as there are many other dimensions to affirmative action beyond mismatch not examined in this paper. Ultimately, the merits and demerits of affirmative action programs must be equally considered in deciding its societal utility as a program to rectify real or perceived racial injustice and historical discrimination.

[21] States have already implemented “percentage plan” programs to increase minority enrollment rates.
[22] Currently, Californian voters are deciding the fate of Proposition 16, a voter-led initiative to reverse the racial preference bans enacted by Proposition 209 and reinstate affirmative action programs.

References

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. "Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program." *Journal of the American Statistical Association* 105, no. 490 (2010): 493-505.

Antonovics, Kate, and Ben Backes. "The effect of banning affirmative action on college admissions policies and student quality." *Journal of Human Resources* 49, no. 2 (2014): 295-322.

Arcidiacono, Peter. "Affirmative action in higher education: How do admission and financial aid rules affect future earnings?" *Econometrica* 73, no. 5 (2005): 1477-1524.

Arcidiacono, Peter, Esteban M. Aucejo, and Ken Spenner. "What happens after enrollment? An analysis of the time path of racial differences in GPA and major choice." *IZA Journal of Labor Economics* 1, no. 1 (2012): 5.

Arcidiacono, Peter, Esteban Aucejo, Patrick Coate, and V. Joseph Hotz. "Affirmative action and university fit: Evidence from Proposition 209." *IZA Journal of Labor Economics* 3, no. 1 (2014): 7.

Arcidiacono, Peter, Michael Lovenheim, and Maria Zhu. "Affirmative action in undergraduate education." Annu. Rev. Econ. 7, no. 1 (2015): 487-518.

Arcidiacono, Peter, Esteban M. Aucejo, and V. Joseph Hotz. "University differences in the graduation of minorities in STEM fields: Evidence from California." *American Economic Review* 106, no. 3 (2016): 525-62.

Arcidiacono, Peter, and Michael Lovenheim. "Affirmative action and the quality-fit trade-off." *Journal of Economic Literature* 54, no. 1 (2016): 3-51.

Backes, Ben. "Do affirmative action bans lower minority college enrollment and attainment? Evidence from statewide bans." *Journal of Human Resources* 47, no. 2 (2012): 435-455.

Baker, Dominique J. "Pathways to racial equity in higher education: Modeling the antecedents of state affirmative action bans." *American Educational Research Journal* 56, no. 5 (2019): 1861-1895.

Bowen, William G., Derek Bok, and Glenn C. Loury. *The Shape of the River*. Vol. 4. Princeton, NJ: Princeton University Press, 1998.

Bound, John, and Sarah Turner. "Cohort crowding: How resources affect collegiate attainment." *Journal of Public Economics* 91, no. 5-6 (2007): 877-899.

Card, David, and Alan B. Krueger. "Would the elimination of affirmative action affect highly qualified minority applicants? Evidence from California and Texas." *ILR Review* 58, no. 3 (2005): 416-434.

Cortes, Kalena E. "Do bans on affirmative action hurt minority students? Evidence from the Texas top 10% plan." *Economics of Education Review* 29, no. 6 (2010): 1110-1124.

Dale, Stacy Berg, and Alan B. Krueger. "Estimating the payoff to attending a more selective college: An application of selection on observables and unobservables." *The Quarterly Journal of Economics* 117, no. 4 (2002): 1491-1527.

Dillon, Eleanor Wiske, and Jeffrey Andrew Smith. "Determinants of the match between student ability and college quality." *Journal of Labor Economics* 35, no. 1 (2017): 45-66.

Hill, Andrew J. "State affirmative action bans and STEM degree completions." *Economics of Education Review* 57 (2017): 31-40.

Hinrichs, Peter. "The effects of affirmative action bans on college enrollment, educational attainment, and the demographic composition of universities." *Review of Economics and Statistics* 94, no. 3 (2012): 712-722.

Hinrichs, Peter. "Affirmative action bans and college graduation rates." *Economics of Education Review* 42 (2014): 43-52.

Kane, Thomas J. "Racial and ethnic preferences in college admissions." *Ohio St. LJ* 59 (1998): 971.

Light, Audrey, and Wayne Strayer. "Determinants of college completion: School quality or student ability?" *Journal of Human Resources* (2000): 299-332.

Long, Mark C. "Race and college admissions: An alternative to affirmative action?" *Review of Economics and Statistics* 86, no. 4 (2004): 1020-1033.

Loury, Linda Datcher, and David Garman. "Affirmative action in higher education." *American Economic Review* 83, no. 2 (1993): 99-103.

Loury, Linda Datcher, and David Garman. "College selectivity and earnings." *Journal of Labor Economics* 13, no. 2 (1995): 289-308.

Sowell, Thomas. *Affirmative Action Around the World: An Empirical Study*. Yale University Press, 2004.

Appendix

Table 6: Descriptive Statistics of Variables Used

	Descriptive Statistics, Whole Sample					
Variables	N	Mean	Median	Min	Max	SD
Six Year Graduation Rate, Overall	28,560	0.567	0.557	0.00340	1	0.178
Six Year Graduation Rate, White	28,560	0.588	0.583	0.00230	1	0.176
Six Year Graduation Rate, Asian	28,560	0.601	0.594	0.00460	1	0.228
Six Year Graduation Rate, Black	28,560	0.468	0.439	0.00350	1	0.226
Six Year Graduation Rate, Hispanic	28,560	0.525	0.500	0.00550	1	0.223
Institutional Admission Rate	28,560	0.661	0.693	0.0473	1	0.189
Majority Vote Dummy	28,560	0.0251	0	0	1	0.157
Ban Discussion Dummy	28,560	0.0267	0	0	1	0.161
Ban Dummy	28,560	0.0384	0	0	1	0.192
Highly Selective Dummy	28,560	0.106	0	0	1	0.308
Moderately Selective Dummy	28,560	0.0936	0	0	1	0.291
Unselective Dummy	28,560	0.800	1	0	1	0.400
Top X% Dummy	28,560	0.0805	0	0	1	0.272
Public University Dummy	28,560	0.382	0	0	1	0.486

Notes: Full sample (private + public) descriptive statistics from which other interaction terms are generated. The number of observations is denoted “N,” and the Standard Deviation is denoted “SD.” “Six Year Graduation Rates” are the percentage of full-time, first-time students at the university or within a specific racial group that graduated in six years or less. Certain institutions reported extremely low or extremely high (100%) graduation rates to the NCES.

Table 7: Summary Statistics by Sample and Sub-Sample

	Ban States		
	Pre-Ban	Post-Ban	Nonban States
Average SAT Score	1077.9	1100.1	1076.6
	(111.3)	(140.3)	(123.4)
Average Six-Year Graduation Rate	51.3%	58.0%	53.7%
	(16.6%)	(18.0%)	(18.4%)
Median Family Income	$49,672.7	$59,728.6	$57,612.1
	($15,504.4)	($20,061.6)	($21,491.0)
Federal Student Loan Recipients	57.7%	53.4%	57.5%
	(14.4%)	(16.3%)	(18.0%)
Share Female Students	57.3%	57.8%	58.2%
	(10.8%)	(10.5%)	(11.3%)
Share First-Generation	35.4%	34.4%	34.7%
	(9.2%)	(10.6%)	(11.4%)
Average Admission Rate	68.7%	61.2%	67.7%
	(17.2%)	(19.6%)	(18.6%)
Six-Year Transfer Rate	8.0%	8.0%	7.9%
	(14.2%)	(13.7%)	(13.0%)

Notes: Median family income is measured in real 2015 dollars. SAT scores are reported for admitted students, and scores after March 2016 are converted to the pre-2016 scale using concordance tables provided by the College Board. Transfer rates are measured for first-time, full-time students within 150% of the expected time to complete a four-year undergraduate degree. Total shares of enrollment are reported for first-time, full-time, undergraduate degree-seeking students. Data is from IPEDS (1997-2007) at the institutional level. Standard deviations are in parentheses.

Table 8: Major Categories in the Eight-Segment College Board Classification Scheme

Arts and Humanities	**Business**	**Health and Medicine**	**Multi-/Interdisciplinary Studies**
Arts, Visual, and Performing English Language and Literature Languages, Literatures, and Linguistics Philosophy and Religion	Accounting and Finance Business Management Administration Human Resources Sales and Marketing	Health Professions and Related Clinical Sciences	Area, Ethnic, Cultural, and Gender Studies Family and Consumer Sciences Liberal Arts and Sciences, General Studies, and Humanities Multi-/Interdisciplinary Studies Parks, Recreation, and Fitness
Public and Social Services	**Science, Math, and Technology**	**Social Sciences**	**Trades and Personal Services**
Law and Legal Studies Military Public Administration and Social Services Security and Protective Services Theological Studies and Religious Vocations	Agriculture and Related Sciences Architecture and Planning Biological and Biomedical Sciences Communications Technologies Computer and Information Sciences Engineering Engineering Technologies Math and Statistics Natural Resources and Conservation Physical Sciences	Communication and Journalism Education History Library Science Psychology Social Sciences	Construction Trades Mechanic and Repair Technologies Personal and Culinary Services Precision Production Trades Transportation and Materials Moving

Notes: Major classification scheme used by the College Board, presented in an abridged version.